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Interim Report For:

OPERATOR ALERTNESS/WORKLOAD ASSESSMENT USING STOCHASTIC MODEL-BASED ANALYSIS OF MYOELECTRIC SIGNALS

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This interim report documents the work done to this point on Autoregressive Integrated Moving-Average (ARIMA) model-based analysis of myoelectric signals. The ARIMA modelling procedure and the hardware required for collecting myoelectric data are described in detail. Pattern analysis methods for characterizing the myoelectric signals under different levels of alertness/workload are discussed. Additionally, the various tasks in the Experimental Control Package that subjects must perform while being monitored are described. Finally, an analysis of data obtained during experimental sessions is provided giving some indication of discriminability of the ARIMA signatures over different task difficulty levels and subjects. Results of this analysis indicate that the first AR parameter is the most useful feature in differentiating workload/alertness level. Additionally, this feature was shown to be reliable (i.e., repeatable) for each underlying level of alertness or load in a given task.

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1. INTRODUCTION

1.1 Overview of the Report

This report summarizes the first phase program activities of a three-year program of research and development directed toward the analysis and evaluation of myoelectric signals (MES) as indicators of operator alertness, and potentially workload in aircraft piloting tasks. The purpose of the study is to investigate the efficiency of stochastic models such as autoregressive (AR), autoregressive-moving-average (ARMA) and autoregressive integrated moving average (ARIMA) models in characterizing the MES under different levels of task imposed burden.

The specific objectives of this effort are:

(1) To develop/adapt state-of-the-art stochastic models for characterizing myoelectric signal patterns.
(2) To investigate under controlled experimental conditions if meaningful repeatable quantitative relationships can be identified between MES patterns and operator loading.
(3) To experimentally identify muscle sites that provide reliable MES signatures.
(4) To develop methods and procedures for "tuning" the models and possibly "filtering out" pattern variations due to variables in electrode locations and individual biases.
(5) To develop guidelines for automatically assessing operator alertness level from the MES temporal signature in piloting tasks.

The three year R&D program builds on the research performed by Madni (1978, 1981) and Graupe; et al (1975, 1977). The results of these research works established the feasibility of stochastic models in characterizing sampled myoelectric signal waveforms. In particular, the work of Madni established the feasibility of stochastic models in characterizing myoelectric signals under varying levels of muscle tension and fatigue. The work reported here consists of findings and results associated with the program's first phase. The specific areas covered are: (1) the model development (2) the system implementation and (3) preliminary experimental evaluation of ARIMA model-based analysis of myoelectric signals and its relationship to task performance. Thus far the model has been implemented in Perceptronics' myoelectric data collection laboratory and preliminary experiments have been conducted to determine the diagnostic capability of the model. Work is currently underway to build on and extend the current experimental work both to provide a firm analytical and experimental basis and to develop techniques for improved data interpretation and algorithmic accuracy.

1.2 Problem Statement

The definition and derivation of objective measures for assessing workload, attentional demands or operator alertness in specific piloting tasks has been an area of investigation by several researchers for more than three decades. Myoelectric signals (MES) have been the object of study by some researchers (Kennedy and Travis, 1947; Travis and Kennedy, 1947; Kennedy, 1953) searching for a physiological indication of alertness in piloting tasks. The results of these experiments demonstrated that there appeared to be some correlation between MES properties (e.g., spike amplitude, zero crossings) and human alertness; however, the use of these properties as an indicator of alertness level was never successfully incorporated in a practical setting primarily because of the excessively high false positives in certain tasks, i.e., diminished alertness was identified in many situations when the subject was perfectly alert. One plausible explanation

for this unreliability in "answers" extracted from MES signatures is that the information content of the original MES waveform is underutilized. In other words, the reliability of features, the information content of the features, and the feature extraction process are critical to the success of the alertness/workload level discrimination process.

1.3 Major Hypotheses and Modelling Approach.

Stochastic modelling and time series analysis methods have been extensively used to statistically model the relationship between the amplitude of a signal at different points in time along the entire time history. In this model, *fluctuations* in amplitude along the timeline are treated as a stochastic process. Stochastic models are particularly well-suited as a temporal feature extraction tool for time varying random signals. Features thus extracted retain sufficient information from the original signal and, consequently, are known to succeed in terms of feature diagnosticity in applications where purely spectral or ad hoc feature extraction methods have failed (Madni, 1978). The key hypotheses underlying the use of stochastic models as a feature extraction method for identifying operator alertness levels are that: (1) at least one model coefficient (feature) will be relatively constant and repeatable for the mental load category and task during which the signal was recorded; and (2) at least one of these nearly constant features associated with each alertness category/load condition will be sufficiently different for each load category thus allowing identification of the category.

Stochastic modelling is well-suited to modelling physiological data that possess one or more of the following characteristics:

(1) The data trace is noisy, i.e., data points show random fluctuations in amplitude and are thus amenable to being modelled as a random sequence.

(2) The classification problem is restricted to a finite, previously established number of categories.

(3) Simpler feature extraction methods such as power spectrum analysis, root-mean-square-value estimation and signal amplitude coding fail to provide good separation among the classes.

The key research problems forming the basis of this study and underlying the use of stochastic models as a feature extraction method are:

(1) The MES recorded from selected muscle groups are correlated with internal states of the human operator, e.g., alertness level or mental load; consequently, the underlying operator state can potentially be reliably diagnosed/inferred via features extracted from the corresponding MES signatures.

(2) The Feature extraction process associated with stochastic model characterization of the MES waveforms is potentially capable of "capturing" features that are both <u>repeatable</u> and <u>diagnostic</u>. Repeatability implies that there is at least one parameter in the stochastic model characterization of MES data that is constant or near-constant for each underlying level of alertness or load in a given task. Diagnosticity implies that these nearly invariant features are sufficiently different for each level of alertness, thereby allowing identification of the underlying operator state.

1.4 Background

The MES within the context of human performance and workload has been studied by various researchers over the last three decades. Within the context of human performance, the MES can be potentially used to provide a measure of either activity of the muscles or the tension of the muscles. When workload estimation is involved, data processing of some kind has to be performed on the raw MES data. This processing can range from conventional signal processing and filtering methods to temporal feature extraction and pattern analysis methods.

A number of studies have been carried out to demonstrate the practical value of MES as a measure of task workload and performance quality. Among the earliest research is that of Kennedy and Travis (1947, 1948, 1949) who found that the level of the integrated MES recorded over the supraorbital facial area was closely related to vigilance and tracking performance. Lucaccini (1968) observed similar changes in the integrated forearm flexor muscle MES during simple and complex visual tasks. He also reported that the average intrasubject correlations between MES and performance were highly significant in both tasks ($r = .21$ and $.30$ in simple and complex tasks, respectively). Stern (1966) found that integrated neck MES rose initially and fell thereafter during easier and more difficult (lower signal frequency) versions of a simple visual task.

It seems from these results that integrated MES voltage is one of the better predictors of vigilance performance, but it has not been universally accepted that MES varies directly with vigilance task performance. Eason et al (1965) interpreted their results as indicating that sympathetic activity decreases along with CNS arousal and vigilance, but that somatic activity increases as part of a compensatory process. Groll's conclusions

(1966) were essentially the same. Yet, judging from their results and the contradictory findings of others, muscle tension, like performance, may reflect both the processes underlying declines in vigilance performance and those acting to counteract.

Jex and Allen (1970) found that rectified and suitably filtered MES's recorded from the forearm of subjects showed a decrease in amplitude when subjects changed from a resting to a tracking state. These researchers also found that grip pressure was found to increase with increase in tracking difficulty. Sun et al (1976) and Stackhouse (1976) found that MES from the forehead and the forearm were correlated with task loading in a variety of aircrew tasks. Madni (1978) found a stable correlation between MES recorded during isometric contraction of the deltoid muscle at various load levels and the parameters of the stochastic models used to characterise the MES waveform.

Luciani et al (1983) at the Aerospace Medical Research Laboratory at the Wright-Patterson AFB explored the use of the Fast Fourier transform to determine operating fatigue by analysis of the center frequencies and amplitudes of the sampled power spectra. These researchers indicate that while they were successful at optimizing the acquisition and processing of the MES, reproducibility of data, especially in a dynamic environment, remained a challenging task. Kranz et al (1983) examined the frequency content of the MES when subjects performed 45-sec contractions of the thenar muscles. The median frequencies (Fm) of surface-recorded MES and compound action potentials were similar early (P greater than 0.6) and late (P greater than 0.5) in the contractions. There was a mean decrease in the Fm during contraction of 39% for 0.1). The Fm of the MES increased 11% (P less than 0.02 to 100% of maximum. Only one of five subjects showed evidence of increasing synchronization of motor unit discharge during contraction. There was no evidence that delay or dispersion of action potential propagation in terminal nerve fibers or at the neuromuscular

junction had a significant effect on frequency content. The findings indicated that the spectral content of muscle electrical activity, and its shift during contraction, primarily reflects intrinsic muscle properties.

Lindstrom et al (1983) studied localized muscle fatique in the masseter muscle with a method based on power spectrum analysis of MES. They found that under the influence of fatiguing contractions, a gradual shift of the spectral curve occurred; the rate of change was taken as a measure of the development of fatigue. The fatigue was dependent on the bite force. The existence of a threshold value of force, below which significant myoelectric fatigue changes do not develop, was shown.

Phillips et al (1983) studied quantitative electromyography techniques in evaluating the response of the neck muscles to conventional helmet weighting (physical fatigue). Their results indicate that the EMG of neck muscles can be used as a noninvasive, objective and quantitative index of the neck muscle fatigue.

Christakos (1982) conducted a study of the electromyogram using a population stochastic model of the skeletal muscle. The researcher studied the features of the electromyogram (EMG) using a population model of skeletal muscle based on the differing properties and the independent activation of motor units (MUs). He showed both analytically and by computer simulation, that: (a) The power spectrum of the EMG is determined by the distribution of filtering and firing properties of the active MUs. (b) A tendency towards a rhythmical grouping of action potentials is to be expected from a set of asynchronous MUs firing semiregularly at similar rates; the grouped electrical activity has a phase-lead over the force output of the set of about 180 degrees. He provided a unified explanation of the properties of the muscle force waveform and the electromyogram, in terms of asynchronous activity of MUs, is proposed. The explanation covers the relationship and the differences between the two signals.

1.5 Stochastic Models

Stochastic modelling (also referred to as time series analysis) has been used extensively to model the statistical relationship between the amplitude of a signal at any point in time and the preceding amplitudes along the time history (Box et al, 1970). The amplitude fluctuations along the time line are treated as a stochastic process. The future course of the process is presumed to be predictable from information about its past.

Before describing these models, the notation employed will be summarized.

- Let

  $$\ldots . X_{k-1} X_k X_{k+1} \ldots .$$

  be a discrete time series where X_i is the random variable X at time i. We denote the series by [X].

- Let μ be the mean of [X], called the level of the process.

- Let [x] denote the series of deviations about μ; that is,

  $$x_i = X_i - \mu$$

- Let [w] be a series of outputs from a white noise source with a mean zero and variance σ^2.

- Let B be the "backward" shift operator for the deviation series such that

$$\boxed{\begin{array}{c} Bx_k = x_{k-1} \\ \text{Hence, } B^m x_k = x_{k-m} \end{array}}$$

- Let ∇ be the backward difference operator for the deviation series such that

$$\boxed{\begin{array}{c} \nabla x_k = x_k - x_{k-1} = (1-B)x_k \\ \text{Hence, } \nabla^m x_k = (1-B)^m x_k \end{array}}$$

The dependence of the current value x_k on the past values of x and w can be expressed in different ways giving rise to several different models.

(a) <u>Autoregressive (AR) Models</u>. In this model the current value of x depends on the previous p values of x and on the current noise term w. Thus,

$$\boxed{\begin{array}{c} x_k = a_1 x_{k-1} + a_2 x_{k-2} + \dots + a_p x_{k-p} + w_k \\ \text{or} \quad x_k = \sum_{i=1}^{p} a_i x_{k-i} + w_k \end{array}}$$

The series [x] as defined above is known as the autoregressive process of order p. The name "autoregressive" arises from the model's similarity to regression analysis and the fact that the variable x in an AR model is regressed on previous values of itself.

(b) Moving Average (MA) Model. In the equation for the AR model, x_{k-1} can be eliminated from the expression for x_k by substituting

$$x_{k-1} = a_1 x_{k-2} + a_2 x_{k-3} + \ldots + a_p x_{k-p-1} + w_{k-1}$$

This process can be repeated to eventually yield an equation for x_k as an infinite series in the w's. A moving average model allows a finite number q of previous w values in the expression for x_k. This formulation explicitly treats the series as being observations on linearly filtered Gaussian noise. A MA process of order q is given by

$$\boxed{x_k = \sum_{i=1}^{p} b_i w_{k-i} + w_k}$$

(c) Mixed Model: Autogressive-Moving Average (ARMA) Model. To achieve flexibility in the fitting of actual time series, this model includes both the AR and the MA terms. A (p,q) ARMA model has the form:

$$\boxed{x_k = \sum_{i=1}^{p} a_i x_{k-i} + w_k - \sum_{i=1}^{p} b_i w_{k-i}}$$

In all three models described above the process generating the series is assumed to be in equilibrium about a constant mean level. Models characterized by such an equilibrium condition are called stationary models. Functional separation of MES using this model has been tried as a means of prosthesis control (Graupe, et al, 1975).

In certain time series data, the level μ does not remain constant, i.e., the series is nonstationary. The series may, nevertheless, exhibit homogeneous or stationary behavior after the differences due to level drift have been

accounted for. It can be shown that such behavior can in certain instances be represented by an autoregressive-integrated-moving-average (ARIMA) model.

(d) Autoregressive-Integrated-Moving-Average (ARIMA) Model. The general (p,d,q) model has the form

$$\boxed{\nabla^d x_k = \sum_{i=1}^{p} a_i \nabla^d x_{k-i} + w_k - \sum_{j=1}^{q} b_j w_{k-j}}$$

where x_k is the original time series

∇ is the backward difference operator

d is the number of differencing operations performed on the original data.

p is the order of the autoregressive terms

q is the order of the moving average terms

If $y_k = \nabla^d x_k$

Then $y_k = \sum_{i=1}^{p} a_i y_{k-i} + w_k - \sum_{i=1}^{p} b_i w_{k-i}$

This model is referred to as a general (p,d,q) model referring to a general pth order autoregressive dth data differencing, qth order moving average process (Box et al, 1970).

1.6 ARIMA Models in MES Characterization

The feasibility of ARIMA Stochastic Model Identification for feature extraction was explored by Madni (1978). The key elements of this study are provided in the following paragraphs.

The experimental data consisted of MES records from the deltoid muscle for different isometric contraction levels. These ranged from 0% to 100%, where 100% tension is defined as 100% of the force generated at maximum effort, not 100% of MES. The primary assumption in this experiment is that an X% run corresponds to X% of muscle tension which is proportional to abduction, and that the only muscle involved in abduction is the deltoid.

The results of the spectral analysis performed on the experimental data revealed a gradual but definite shift of power to lower frequencies with increase in muscle contraction. The total power of the signal was found to lie below 2500 Hz. The most significant shift of power to lower frequencies with increasing muscle tension was observed in the frequency band that contained ninety percent of the total power.

ARIMA models were fitted to the MES data recorded for each contraction level. The ARIMA parameters were fitted across the n trials for each contraction level. It was found that the AR terms were relatively constant for the 1%, 5% ..., 50% tension levels; however, the AR coefficients for the 100% tension level were quite different (both in sign and magnitude) from those for all other tension levels. These and other findings (Graupe, 1975) provided the impetus for exploring the stochastic modelling approach as a viable feature extraction tool.

1.7 Program Objectives for the First Phase

The specific objectives of the first phase of the current program are:

(1) To develop an ARIMA stochastic model-based approach for identifying operator alertness and workload levels.

(2) To develop and implement stochastic model-based MES pattern analysis software within the overall data acquisition and processing system.

(3) Develop an experimental plan and a representative task simulation and interface.

(4) Perform the pilot experiment investigation.

(5) To identify model structure, via model parameter identification processes.

(6) To evaluate the model-derived features in terms of their relevance to, or association with operator alertness level and/or mental load.

2. SYSTEM IMPLEMENTATION AND EXPERIMENTAL SET-UP

2.1 Overview

This chapter gives a description of the hardware and instrumentation currently used, our selection criteria, and the modifications required to integrate the overall system. The software modules required to perform the ARIMA identification process are described in detail along with an explanation of the Box and Jenkins identification procedure. Also included is a summary of the ARIMA model identification process and the system software.

2.2 Hardware And Instrumentation

2.2.1 Development System Selection. Very early in the project, we made the decision to separate the computer system into two major components. One subsystem would be responsible for collecting MES data while the subject was performing a prescribed task. This same system would be used to analyze the collected MES data (off-line) after termination of the experiment. By using the same system for both data collection and analysis, we bypass the problems associated with transfering large data files between systems. A second subsystem would be responsible for controlling the experiments and collecting behavioral performance data during the experiment.

We considered a number of systems that were potentially suitable for MES data acquisition and analysis, and the required software development. Our experience with microcomputers based on 8-bit processors was that they had inadequate speed for performing complex computations. Consequently, we decided upon the 16-bit microcomputer family within which we evaluated several alternatives.

We favored 16-bit micros that support the UNIX operating system. This was done for three main reasons. First, UNIX is a known and popular system for experimental software development. Second, the specific file management facilities available under UNIX provide us with an efficient way of creating and maintaining the integrity of the various program and data files. Third, we had significant experience with the UNIX operating system and foresaw a shortening of the software development time under UNIX. Of the three popular 16-bit microcomputers, i.e., Motorola's 68000, Intel's 8086, and National's 16000, only Motorola supported the UNIX operating system at the time of system selection. Our next major decision was to decide on a specific 68000-based development system and vendor. Of the 68000 based systems supporting UNIX, we identified eight candidates: Codata Corp.; Callan Data Systems; COSMOS Systems, Inc.; Cromemco, Inc.; Fortune Systems; Forward Technology, Inc.; Plexus; and Dual Systems Corp. Our criteria for selecting the system was three-fold: cost, availability and support by vendor. We selected the COSMOS system on the basis of immediate availability, support by a Northern California-based vendor, and relatively competitive price.

There is an upper limit of 16M bytes of memory that can be addressed with the 24-bit addressing capability of the Motorola 68000. We needed adequate memory to run the ARIMA algorithm which requires large arrays for data storage. At least 256K bytes were needed for this algorithm plus the operating system. We thus decided to opt for either 256K bytes or 512K bytes of RAM, depending on the basic 68000-based system's minimal memory configuration.

Additionally, a large amount of hard disk storage was required for storing the large MES data files in addition to all of the data collection and ARIMA analysis program files. We calculated that we would require at least a 20M byte hard disk.

We also required a system which had a widely used bus so that we could add peripheral boards; in particular, we needed a good Analog-to-Digital Convertor board to collect and digitize MES data. Candidates busses were the Q-bus and Multibus. Of the two, Multibus had the greatest number of peripheral boards available.

As indicated, we confined ourselves to systems that supported UNIX. In addition we decided to do the software development in the C language. C is a medium level language. That is, it supports high level commands but executes almost as fast as assembly language. C therefore allows efficient coding (both in terms of memory requirements and execution time) at both a high-level (i.e., algorithms) and a low level (i.e., device "drivers") of coding.

The MULTIBUS-based COSMOS CMS16/UNX system we selected has the following hardware and software capabilities: 68000 CPU with DMA and vectored interrupt capability and memory management hardware, 512k Bytes RAM, eight RS-232 serial parts, real-time clock, one 40M Byte hard disk system, one 25M Byte fixed/25 M Byte removable hard disk subsystem, one Hazeltine Esprit terminal. Software included: UNIX version 7 operating system with Berkeley extensions (multi-user, multi-tasking), C programming language, 68000 assembler and various UNIX utilities (i.e., editor, linker, debugger, etc.).

In addition to our 68000 based system we needed a low cost computer with graphics capability to support task presentation and performance monitoring software. We decided on a multiprocessing architecture using both the COSMOS and an Apple IIe. We partitioned the role of the two processors in such a way that the 68000 system was used only for data collection and subsequent analysis and the Apple was used for realtime task presentation and

and performance monitoring. Along with our Apple IIe system we purchased a GRAFORTH (a good graphics oriented language) compiler to support the graphics requirements associated with the experimental tasks.

The Apple IIe was obtained from COMPUPLUS. Equipment included the basic computer with an 80 column card, 64k Bytes of RAM, an Apple monochrome monitor with stand, two floppy disk drives, two RS232 serial interfaces, a parallel interface, a joystick, and an OKIDATA 82A line printer.

Functionally, the data collection and analysis is performed by the Motorola 68000. The actual experiment is displayed on the Apple monitor and the user responds with either a button pad or joystick attached to the IIe. The two systems communicate with each other over an RS-232 interface cable.

2.2.2 Analog-to-Digital Board Selection and Hardware Interface. Central to this experiment was the requirement to collect analog myoelectric signals which are sampled, digitized, and stored for future analysis. Sampling and digitizing the MES was performed by an Analog Devices RTI-711 A/D board. It was found that the A/D board had to be modified slightly to respond to the MULTIBUS read/write signals generated by the COSMOS CPU board. This modification was made and the A/D board was successfully debugged. A device driver program described in detail in Section 2.3.5 was written and integrated with the UNIX operating system.

The off-the-shelf A/D board comes with a 16.384 KHz crystal controlling the clock rate. We replaced the standard crystal with one capable of generating a 32.768 KHz clock rate. This gave us a maximum sampling rate under interrupt control of 2048 samples per second. This implies that if we wish to sample N multiplexed channels, the sampling rate of each channel would be 2048/N.

2.2.3 Electrode Selection and Interface Design. In the selection of electrodes, we decided against using the standard disposable type of EMG electrodes because they would require the purchase or construction of a multi-channel, high performance instrumentation amplifier. We instead decided to use EMG electrodes with the signal processing circuitry resident in a common package. The electrodes were supplied by Motion Control Incorporated of Salt Lake City. They consist of differential inputs spaced 3.5 cm apart, a central ground tap and a high performance EMG preamplifier in a single package. The preamplifier characteristics are shown in Table 2-1:

TABLE 2-1

PREAMPLIFIER CHARACTERISTICS

- Gain - 360 @ 500 Hz.
- CMRR - 102dB @ 500 Hz.
- Frequency Response - Flat from 10Hz to 42KHz
- Input impedance - 100,000 Megohms
- Power requirements $\pm$ 6-15 VDC.

While the electrical characteristics of these electrodes were indeed impressive, their physical size (5cm x 1.5cm x 0.8cm) precluded the use of certain desirable muscles (i.e., frontalis). In order to eliminate the possibility of ground-loops and to effectively isolate the subjects from the main supply current, a separate battery supply was used to power the electrode circuitry rather than using the supply lines available from the data acquisition system. A box containing the batteries and the hardware necessary to interface the electrodes to the A/D board was constructed. This box also housed the electrode select switches and low battery indicator lamps. These lamps were driven using power from the data

acquisition system supply lines so as not to induce undo power drain on the batteries. A comparator circuit was used to toggle the lamps when battery power fell below a preset level.

2.3 Modelling and System Software

2.3.1 ARIMA Model Identification. As is shown earlier, an ARIMA model for a general time series has d - levels of differencing, p - autoregressive coefficients, and q - moving average coefficients as seen in the equation below:

$$\boxed{\nabla^d Z_t - \phi_1 \nabla^d Z_{t-1} - \cdots - \phi_p \nabla^d Z_{t-p} = a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q}}$$

$\nabla^d Z_u$ is the d^{th} difference of the time series at time u,

a_u is the zero mean, normally-distributed random noise at time u.

ϕ_i is the i'^{th} autoregressive coefficient.

θ_i is the i'^{th} moving average coefficient.

Determination of p, d, and q is a three step procedure. The first step of the ARIMA modelling as provided in Box & Jenkins (1970) is to identify p, d, and q. The specific software module associated with this step calculates autocorrelations and partial autocorrelations for different levels of data differencing. These autocorrelations and partial autocorrelations provide an insight in selecting p, d, and q of the ARIMA model. To determine d, one looks at the autocorrelations for a given level of differencing and observes whether or not they "die out" rapidly. If they do, the given level of differencing is adequate; if not, additional differencing operations are required until this constraint is satisfied. The smallest level of differencing for which the autocorrelations die out rapidly is taken as the optimum level of differencing, d.

To determine p and q we look at the autocorrelations and partial autocorrelations for the selected level of differencing. Box and Jenkins summarize this approach as follows:

> "Briefly, whereas the autocorrelation function of an autoregressive process of order p tails off, its partial autocorrelation function has a cutoff after lag p. Conversely, the autocorrelation function of a moving average process of order q has a cutoff after lag q, while its partial autocorrelation tails off. If both the autocorrelations and partial autocorrelations tail off, a mixed process is suggested. Furthermore, the autocorrelation function for a mixed process, containing a p^{th} order autoregressive component and a q^{th} order moving average component, is a mixture of exponentials and damped sine waves after the first q-p lags. Conversely, the partial autocorrelation function for a mixed process is dominated by a mixture of exponentials and damped sine waves after the first p-q lags."

Once p, d, and q are selected, we proceed to the second stage of the model identification process. The purpose of the second stage is to come up with initial estimates of the autoregressive and moving average parameters. These initial estimates are then used by the third stage of the model in generating final estimates of the autoregressive parameters. The result of this three stage process is a feature vector consisting of a small number of parameters that characterize the original MES time series data.

Each of the three stages of the ARIMA model identification process were coded and tested on three sets of sample data associated with illustrative examples in Box & Jenkins. After appropriate debugging, we were able to reproduce the values for autocorrelations, partial autocorrelations and

intermediate and final values for autoregressive and moving average parameters for each of these sample data sets. A detailed description of the specific algorithms implemented is given in the following section.

2.3.2 ARIMA Software Development. As there was no ARIMA software available for immediate implementation on a microcomputer, we decided to write our own ARIMA package. We decided to go the micro rather than minicomputer route for three main reasons. First, we wanted a dedicated system in a laboratory environment where we could collect data in realtime, analyze the data off-line and then run future data in realtime with realtime recognition software. A microcomputer implementation allows us this flexibility. Second, the portability and cost factors made microcomputers an attractive proposition. Finally, we had both language and operating system of choice (C and UNIX) available on the microcomputer. In developing new software, one always has to face the problem of software program validation. In order to do this, we needed both detailed algorithms and test data that had been generated with the algorithms. To this end, we selected Box and Jenkins' *Time Series Analysis* (1970). This book contains detailed algorithms, trial data and results. Consequently, the problem became one of writing the C-code corresponding to these algorithms, running the trial data through the various stages of the ARIMA model identification process and comparing the results generated on our microcomputer implementation with those in the Box and Jenkins example problem solution.

We began collecting data from subjects with a 2 KHz sampling rate. What we found however is that we were getting ARIMA models with an extremely large number of autoregressive coefficients before cut-off, after some reflection, we decided that this was because the predominant information was around 100 KHz. This meant that the autocorrelations and the partial autocorrelations were relatively large out to about 20 terms. Since

autoregressive coefficients are closely related to partial autocorrelations we would need a model with around 20 autoregressive terms to capture all the significant autoregressive coefficients.

We therefore decided that we were oversampling for the purpose of modelling the predominant information with a parsimonious ARIMA model. We thus cut the sampling frequency to 1 KHz so that autocorrelations and partial autocorrelations would be relatively large out to about 10 terms only. This gave us about half the number of autoregressive coefficients.

2.3.3 ARIMA Model Implementation. The ARIMA Model Implementation is based on Box & Jenkins (1970). The model is implemented in C and consists of the following 3 software packages:

(1) PDQ Estimator. This software package allows the experimenter to estimate the number of levels of differencing and the number of autoregressive and moving average parameters (i.e., derive p, d, and q) required to fit the data.
(2) INITARMA Estimator. This software package provides initial estimates of autoregressive and moving average parameters.
(3) ARMA Estimator. This software package provides the maximum likelihood estimates of the autoregressive and moving average parameters.

Each software package is described in turn in the following sections.

PDQ Estimator

The user employs this software package to help in determining the number of levels of differencing (d), the number of autoregressive parameters (p), and the number of moving average parameters (q) required to model a given time series. This package produces data for the user, which the user examines to select p, d, & q.

Each level of differencing from 0 up to a fixed integer value supplied by the user is computed as follows:

$$X_K = \hat{X}_{K+1} - \hat{X}_K \qquad 1 \le K \le N,$$

where N = total number of points in $\{\hat{X}_K\}$ and $\{\hat{X}_K\}$ is the set of all values in the time series. Subsequently, a zero mean transformation is applied to the time series by setting $W_K = X_K - \mu$, where

$$\mu = \frac{1}{N} \sum_{K=1}^{N} X_K$$

The resulting zero mean time series is used in all subsequent computations. First, the autocovariances (C_K) up to a specified lag are computed by:

$$C_K = \frac{1}{2} \sum_{t=1}^{N-K} (W_t \cdot W_{t+K})$$

Then, the autocorrelations (r_K) are computed by:

$$r_K = C_K/C_0$$

The standard errors of autocorrelations (σ_K) are computed by:

$$\boxed{\sigma_K = \left(\sqrt{1 + 2\left(\sum_{i=1}^{K} r_i^2\right)}\right) / \left(\sqrt{N}\right)}$$

Similarly, partial autocorrelations are computed using the iterative formula given below:

$$\hat{\phi}_{\ell\ell} = \begin{cases} r_1 & \text{when } \ell = 1 \\ \dfrac{r_1 - \sum_{j=1}^{\ell-1} \hat{\phi}_{\ell-1,j}(r_{\ell-j})}{1 - \sum_{j=1}^{\ell-1} \hat{\phi}_{\ell-1,j}(r_j)} & \text{when } \ell = 2, 3, \ldots, L \end{cases}$$

$$\text{where } \hat{\phi}_{\ell j} = \hat{\phi}_{\ell-1,j} - \hat{\phi}_{\ell\ell}\,\hat{\phi}_{\ell-1,\,\ell-j} \qquad j = 1, 2, \ldots, \ell-1$$

Finally the standard error of the partial autocorrelations is computed by $\sigma^2 = 1/\sqrt{N}$.

The user must evaluate the autocorrelations and partial autocorrelations at each level of differencing and decide on p, d, and q. For the evaluation criteria needed to make these decisions, consult Chapter 6 of Time Series Analysis (Box and Jenkins, 1970).

INITARMA Estimator. This software package is used to compute initial estimates of the autoregressive ($\bar{\phi}$) and the moving average ($\bar{\theta}$) parameters. It is fully automated, and when given a p, d, and q as an input, will provide initial estimates of the autoregressive parameters, $\bar{\phi}$, and the moving average parameters, $\bar{\theta}$. The original time series is differenced d times and then made zero mean and the autocovariances (C_K) are computed as before.

The autoregressive parameters are computed by solving the Yule-Walker equations as given below:

$$\bar{A}\bar{\phi}_0 = \bar{X} \quad \text{where } A_{ij} = C_{|q+i-j|},\ X_i = C_{q+1} \text{ for } i, j = 1, 2, \ldots p.$$

Subsequently, modified covariances are calculated by:

$$C_j' = \begin{cases} \sum_{i=0}^{p} \sum_{K=0}^{p} \hat{\phi}_1 \hat{\phi}_K C_{|j+1-K|} & p > 0 \ (\phi_0 = -1) \\ C_j & p = 0 \end{cases}$$

for $j = 0, 1, \ldots, q$.

The Newton-Raphson algorithm is then employed to calculate initial estimates for moving-average values using the recursion relation:

$$\bar{\tau}^{i+1} = \bar{\tau}^{i} - \bar{h}$$

where $\bar{T}^i\bar{h} = \bar{f}^i$.

In simple terms, the value of τ^{i+1} is calculated at the (i+1)st iteration from its value τ^{i} at the ith iteration, where

$$\bar{\tau} = (\tau_0, \tau_1, \ldots, \tau_q), \quad f_j = \sum_{i=0}^{q-j} \tau_i \tau_{i+j} - C_j', \quad \bar{f} = (f_0, f_1, \ldots, f_g),$$

$$\bar{T} = \begin{bmatrix} \tau_0 & \tau_1 & \cdots & \cdots & \tau_q \\ \tau_1 & \tau_2 & & \tau_q & \\ \vdots & & \cdot^{\cdot^{\cdot}} & & \\ \vdots & \cdot^{\cdot^{\cdot}} & & & 0 \\ \tau_q & & & & \end{bmatrix} + \begin{bmatrix} \tau_0 & \tau_1 & \cdots & \cdots & \tau_q \\ & \tau_0 & \tau_1 & & \tau_{q-1} \\ & & \ddots & & \vdots \\ & 0 & & \ddots & \vdots \\ & & & & \tau_0 \end{bmatrix}$$

with starting values $\tau_0 = \sqrt{C_0'}, \tau_1 = \tau_2 = \ldots = \tau_q = 0.$

When $|f_j| < \varepsilon$, $j = 0, 1, \ldots, q$, for some prescribed value ε, the process is considered to have converged and the parameter estimates are obtained from the τ values according to:

$$\theta_j = -\tau_j/\tau_0 \qquad j = 1, 2, \ldots q.$$

Finally, an estimate of the white noise variance is computed in accord with:

$$\hat{\sigma}_a^2 = \begin{cases} \tau_0^2 & p > 0 \\ C_0 - \sum_{i=1}^{p} \hat{\phi}_i C_i & q = 0 \end{cases}$$

ARMA Estimator. This software package is used to compute the maximum likelihood estimates for $\bar{\phi}$ and $\bar{\theta}$. The initial estimates of the autoregressive parameters, $\bar{\phi}$, and moving average parameters, $\bar{\theta}$, are supplied by the user along with the differenced, zero-mean time series.

The maximum likelihood estimates for $\bar{\phi}$ and $\bar{\theta}$ are obtained using the Marquardt Algorithm for Nonlinear Least Squares as modified by G. Wilson. Until such time that convergence has not been achieved, the following sequence of steps are repeatedly performed:

(1) Conditional residuals are calculated from current estimates of $\bar{\phi}$ and $\bar{\theta}$.

(2) The sum squared of the residuals is calculated.

(3) The partial derivatives of the residuals as a function of changes in $\bar{\phi}$ and $\bar{\theta}$ are computed.

(4) The covariance matrix of the current estimates is computed along with a vector based on the partial derivatives and the residuals and a vector of scaling quantities.

(5) New estimates of $\bar{\phi}$ and $\bar{\theta}$ are made.

Each step is discussed in detail below:

Calculating Conditional Residuals

The conditional residuals are easier to compute than the unconditional residuals which involve backforecasting the time series. These conditional residuals are computed according to the following formula:

$$\boxed{a_i = \begin{cases} 0 & i \leq p \\ \{W_i - \sum_{j=1}^{p} \phi_j * W_{i-j} + \sum_{j=1}^{p} \theta_j * a_{i-j}\} & i > p \end{cases}}$$

where M = min(i-1,q), for i = 1,2,...,N.

Calculating the Sum Squared of the residuals

The sum squared of the residuals is calculated by:

$$\boxed{S(\beta_0) = \sum_{i=1}^{N} a_i^2}$$

Calculating Partial Derivatives of the Residuals

Let $\bar{\beta} = (\beta_1, \beta_2, \ldots \beta_K) = (\phi_1, \phi_2, \ldots \phi_p, \theta_1, \theta_2, \ldots, \theta_q)$. Then the partial derivatives of the residuals is calculated by

$$\boxed{X_{i,t} = \{a_t\ (\beta_1, \ldots, \beta_i, \ldots, \beta_K) - a_t\ (\beta_1, \ldots, \beta_i + \delta_i, \ldots, \beta_K)\}/\delta_i}$$

where t = 1, 2, ..., N.

Stage 1: Calculating Covariance Matrix of Current Estimates, Etc.

The covariance matrix of current estimates is calculated by:

$$\boxed{A_{ij} = \sum_{t=1}^{N} X_{it}\ X_{jt},}\qquad \text{where } i, j = 1, 2, \ldots, K.$$

The vector based on the partial derivatives and residuals is computed via:

$$\boxed{g_i = \sum_{t=1}^{N} X_{i,t}\, a_t,} \quad \text{where } i = 1, 2, \ldots, K.$$

The vector of scaling quantities is calculated by:

$$\boxed{D_i = \sqrt{A_{ii}}\,,} \quad \text{where } i = 1, 2, \ldots, K.$$

Stage 2: Making New Estimates of $\bar{\phi}$ and $\bar{\theta}$

The modified and constrained linearized equations $A^* h^* = g^*$ are constructed according to:

$$\boxed{\begin{array}{ll} A^*_{ij} = A_{ij}/D_i D_j & i \neq j, \\ A^*_{ii} = 1 + \pi & \\ g^*_i = g_i/D_i & \end{array}}$$

The equations are solved for h^*, which is scaled back to give the parameter corrections h_j, where

$$\boxed{h_j = h_j/D_j}$$

Then the new parameter values are constructed from

$$\boxed{\bar{\beta} = \bar{\beta}_0 + \bar{h}}$$

and the sum-square of residuals $S(\beta)$ evaluated.

Stage 3:

(1) If $S(\beta) < S(\beta_0)$, the parameter corrections $\bar{h}$ are tested. If all are smaller than ε, convergence is assumed and the KxK matrix A^{-1} is used to calculate the covariance matrix of estimates as described below; otherwise, $\bar{\beta}_0$ is reset to the value $\bar{\beta}$, π is reduced by a factor F_2 and computation returns to Stage (1).

(2) If $S(\beta) > S(\beta_0)$, the constraint parameter π is increased by a factor F_2 and computation resumed at Stage (2). In all but exceptional cases, a reduced sum of squares will eventually be found. However, an upper bound is placed on π, and if this bound is exceeded, the search is terminated.

When convergence is achieved, either according to the criterion in (1) of Stage 3, or it is assumed to have occurred after a specified number of iterations, the residual variance and the covariance matrix of the estimates are computed as follows.

After the maximum likelihood estimates are computed, specific computations providing some indication about the goodness of the estimates are made.

First, the residual variance is calculated by:

$$\hat{\sigma}_a^2 = \frac{1}{(N-p-q)} S(\beta_0)$$

Then, the covariance matrix of estimates is calculated by:

$$V = A^{-1} \hat{\sigma}_a^2$$

Next, the standard errors and correlation matrix is calculated by:

$$S_i = \sqrt{V_{ii}} \qquad i = 1, 2, \ldots, p + q.$$

Then, the correlation matrix is calculated by:

$$R_{ij} = V_{ij} / \sqrt{V_{ii} V_{jj}} \qquad i, j = 1, 2, \ldots, p + q.$$

Using the residuals a_t corresponding to the least square estimates, the residual autocorrelations are obtained from

$$r_{aa}(K) = C_{aa}(K)/C_{aa}(0)$$

where

$$C_{aa}(K) = \frac{1}{N} \sum_{t=1}^{N-k} (a_t - \bar{a})(a_{t+K} - \bar{a}), \text{ where}$$

$$\bar{a} = \frac{1}{N} \sum_{t=1}^{N} a_t,$$

and

$$K = 0, 1, \ldots, (N/10) + p + q.$$

Finally, the chi-square statistic and degrees-of-freedom are calculated by:

$$\chi^2 = N \sum_{K=1}^{(N/10)+p+q} r_{aa}^2(K),$$

$$V = (N/10).$$

2.3.4 Control of Data Analysis. Originally, a package was written to control the analysis of the collected MES data. This package allowed us to serially analyze MES records on a disk file in an interactive fashion. Since the data for one experimental session is contained in a single file with several MES records, this required that the experimenter be present to process each record for the experimental sessions with which he was concerned. Consequently, a batch mode package was written allowing the

experimenter to specify up to 25 files representing 25 experimental sessions and process all the records in these files. This program can either be used to identify the order of the ARIMA model (i.e., find p, d, & q) or to get the preliminary and final estimates of the autoregressive and moving average parameters.

This batch program is particularly useful because at the present time since we do not currently have hardware tied-in to the Motorola 68000 to perform floating-point operations, ARIMA process execution takes several hours. This way we can leave the system running overnight and process the results of many experimental sessions with no operator intervention required.

2.3.5 Analog-to-Digital Driver Program. In order to "communicate" with the A/D board through a program running under UNIX, it was necessary for us to develop a device driver and add it to the drivers in the prior UNIX configuration. The kernel of the operating system consists of a scheduler which is periodically invoked by a hardware interrupt to determine whether or not to parcel out time to any on-going activity. The UNIX kernel is invoked every 10 msec. and executes for approximately 1.0 msec. Since the interrupt rate of the A/D board was over 2kHz, we had to interrupt the UNIX kernel. Since the kernel disables all maskable interrupts, the only way to do this is to use an interrupt channel that can't be locked out -- namely the nonmaskable interrupt.

A driver program for a peripheral device usually consists of various functions which can be executed at a normal rate and an interrupt handler which must be invoked immediately after an interrupt is received and executed quickly without interruption. Since the interrupt itself was given top priority (i.e. - it was non-maskable) we were guaranteed that the interrupt handler would be invoked immediately; however, the interrupt handler had to be streamlined to execute very fast. Thus, this handler was

written in 68000 assembly language. This allowed some time during the approximately 500 sec. between interrupts for background UNIX procedures and data collection software processing.

2.3.6 Development of Data Collection Package. In order to perform offline ARIMA analysis of MES data, the data must be collected and stored during the performance of the experiment. To this end, a data collection package was developed. This package allows the experimenter to select the particular experiment, level of difficulty, and trial. It also allows the experimenter to specify the A/D channels involved and the data files to be used for MES data storage.

When the actual experiment begins, this software sends a code from the Motorola 68000 through an RS232 interface to the Apple IIe in order to initiate the appropriate experiment. At specified intervals, data is then collected through the electrodes attached to the subject, via the A/D, and stored in the experimenter-specified file. After a predetermined time has elapsed, a message is sent to the Apple IIe to terminate the experiment.

3. EXPERIMENTAL STUDY

3.1 Overview

The first series of experiments was designed to assess the "goodness" of model-derived features in terms of their relevance to operator alertness/workload levels. The main vehicle used for this is a computer-based stochastic signal processing and pattern recognition algorithm. In previous sections we have described how a stochastic modeling approach characterizes a myoelectric signal. In this section we will describe the model function validation methods and the specific behavioral issues being investigated via the use of model-based feature derivation/extraction of workload correlates. A task simulation configured to resemble the Criterion Task Set (CTS) workload test battery developed at AFAMRL (Shingledecker, 1983) was developed. Each subject was presented with controlled workload tasks along the perceptual/central processing/motor task dimensions. As the subject performed the various tasks, the MES was recorded at the beginning, the middle and near the end of task execution. At the end of the experiment, model outputs and subject performance and rating comparisons were made between levels of task loading and among various types of tasks.

3.2 Experimental Hypotheses and Test Procedure

In this initial set of experiments, the fundamental question, i.e. whether task loading affects model-derived MES features in some deterministic fashion, was examined. To this end, three basic issues were investigated. The first concern is whether it is possible to find at least one ARIMA model coefficient that has a near-constant magnitude for each underlying loading/alertness level for a given subject, muscle site, and task type. To this end, the model coefficients were examined for invariance across

multiple samples within trials and across multiple trials. Those coefficients that satisfy the above conditions are considered "reliable." The second key issue i.e. whether the features that were considered reliable are also sufficiently different in magnitude for each of the different levels of task demand and for each task category. To this end, the features are examined across the different task types and levels of task demands. The third central issue addressed is the correlation and sensitivity of these features to primary task performance and subjective ratings.

Our two key hypotheses associated with ARIMA stochastic model characterization of MES are that we can potentially uncover both reliable and diagnostic features associated with the MES on the basis of which we will be able to infer the underlying operator state/load.

By feature reliability, we mean that there is at least one set of model coefficients in the ARIMA model that provides invariant or near-invariant pattern values for each subject within each underlying level of alertness/mental load for a given type of task.

By feature diagnosticity, we mean that each of these reliable (invariant or near-invariant) pattern elements is distinctly different (in a statistical sense) for the different levels of task demand and possibly, for different types of tasks. Candidate features are selected from the overall pattern vector to test the hypotheses.

Hypothesis Testing. In the search for reliable features, we ran preliminary test experiments using one subject with repeated runs. Feature reliability and diagnosity were then established in a formal experiment using a repeated measures design. A number of pattern recognition approaches to data analysis can be used to test the significance of both

reliability and diagnosticity of selected features. These include t-test for comparison of group means, Analysis of Variance and chi-square tests for comparison of variable subgroups and partial correlation and clustering of data.

3.3 Experimental Tasks. The central concept of this study is to impose controlled workload tasks while simultaneously recording MES signals from selected muscle site(s). The selection of tasks and procedures was based on the degree to which they satisfy the requirements of: (1) validity and reliability, (2) flexibility and quantifiability, (3) memory, (4) mental mathematics/reasoning, and (5) choice reaction time. This set constitutes the most frequently used criteria in the literature. It also represents a subset of standardized loading tasks under development at AFAMRL. The overall criteria task set (CTS) under development at AFAMRL include the following (note that the CTS is a combination of discrete, independent task components rather than an integrated, continuous game situation such as Perceptronics' earlier simulation of a supervisory air piloting task):

(1) Perceptual tasks.

- Probability monitoring task
- Auditory monitoring task
- visual target search task

(2) Central processing tasks.

- Memory tasks - memory update, memory recall.
- Manipulation and comparison tasks - linguistic processing, mathematical computation, spatial pattern identification.
- Reasoning tasks - analogical reasoning and grammatical.
- Planning and scheduling - flight assessment and supervisory control.

(3) Motor tasks.

- Critical tracking task.

For the MES feature selection study performed in the first phase of our program, we employed a subset of the CTS, selecting only those task components that were already established and validated at AMRL. These components included a probability monitoring task, critical tracking task, and manipulation and comparison task. These task elements are described in the following paragraphs.

(a) Probability Monitoring Task is the monitoring of dynamic processes represented as continously moving indicators. The operator is concerned with whether or not the fluctuating process or condition is maintained within prescribed limits, or a prescribed average value. A typical example in an aircraft is the requirements to monitor the rate of climb indicator in rough air. The operator observes, on a sampling basis, the moment to moment fluctuations in the position of the pointer. The primary interest of the operator response is the perceptual recognition of the occurrence of a change in the average value of the fluctuating pointer. Thus, in addition to assessing a monitoring function, the evaluation of stimulus discrimination is also involved.

The basic display elements (see Figure 3-1) were a number of scales programmed so that the pointer fluctuated in random manner about specified average values. The maximum frequencies represented in the fluctuation of the pointer were somewhat less than 1Hz. The program also allowed for the selection of negative or positive "bias" by the operator using a two-point switch. Thus, if the operator suspected that the average value had departed from the norm, he could use the switch and got immediate feedback as to the correctness of his judgment. Feedback was presented as a stopped

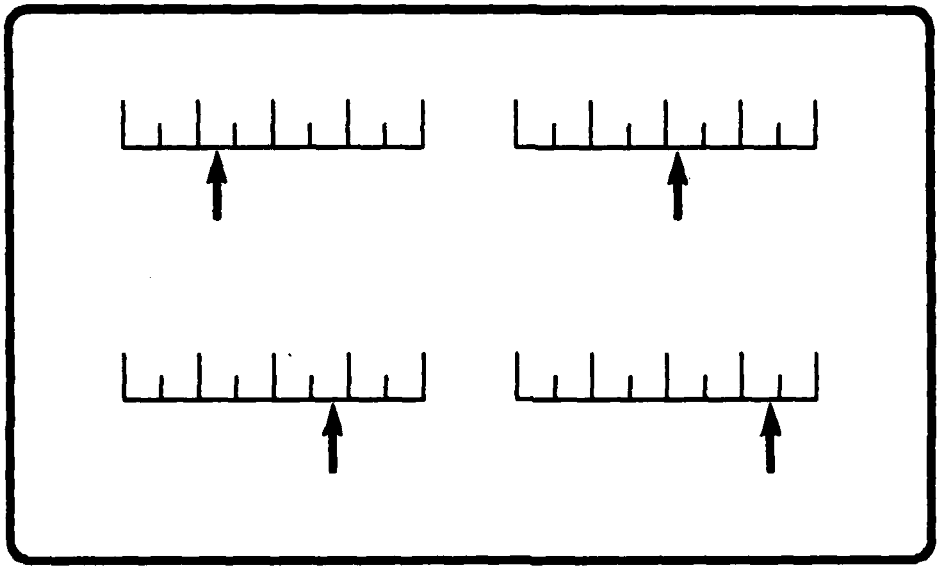

FIGURE 3-1.
PROBABILITY MONITORING

pointer showing true bias and the pointer would move back to unbiased position if his judgment was correct. The manipulation dimensions included the number of dials and the magnitude of the bias (as S/N).

(b) Critical tracking task is a time-honored testing procedure that keeps making a test more difficult until the operator fails to control the unstable process. The level of the test at the failure point is used to define the operator's ability to keep the system stable by carefully adjusting his own control gain. Unlike the critical tracking task system used at AMRL which is "hard-wired", we implemented simulated task conditions in software, representing the system dynamics via a set offirst order differential equations. The standard critical tracking task implemented is described in Figure 3-2. The autopacer system automatically decreases the stability margin monotonically from an initial confortable level. The rate of decrease automatically slows down as the smoothed absolute control error increases. When the task becomes so difficult that control is lost, the value of the stability margin is recorded. The task is simply represented on the screen: the tracked symbol moved dynamically away from the center of the screen, while the center and, the range of the allowable path are shown as the background. The manipulation dimensions includes instability level and the number of the tracking axis.

(c) Manipulation and comparison task. The specific task developed under the category is a linguistic processing task that requires subjects to classify paired stimuli (letters, digits, words or forms) and to press one of two keys (same or different). The level of instruction upon which the subject was to base his classification is varied. The instructions used to define "same" are physical identity (e.g., AA), name identity (e.g., Aa), category identity (e.g., Ae), rhyme (Arrange-Exchange), synonym (Ally-Friend) and antonym (Truce-Conflict). The experiments are designed to allow the same stimulus-response combination (e.g., AB-different) to occur

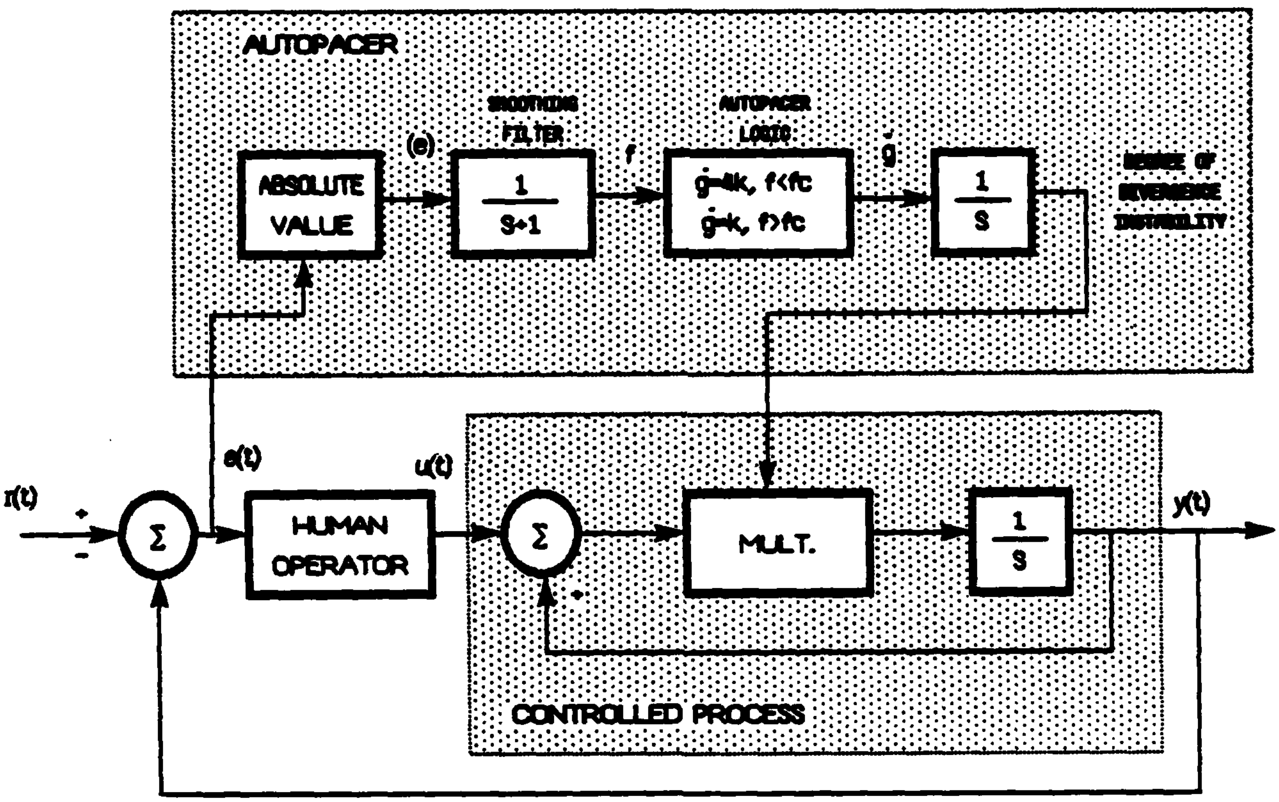

FIGURE 3-2.
SELF-ADJUSTING CRITICAL TASK IMPLEMENTATION

with instructions at quite different levels. These instructions are stored in the computer and retrieved before the onset of the paired stimulus. The manipulation dimensions are the dominant instruction level and the type and population of stimuli.

3.4 Experimental Variables. The experimental hypotheses deal with the statistics of MES feature values, task performance measures (reaction time, and performance accuracy) and rating scales. The following experimental variables and levels were tested:

(1) Task type - three levels.

(a) Perceptual tasks.
(b) Central processing tasks.
(c) Tracking tasks.

(2) Task loading level - two levels.

(a) Low.
(b) High.

The low and high loading levels were adjusted according to the level, and values given to AMRL's CTS implementation. The low loading levels seem to provide sufficient time for the subject's response, while the high loading level is designed to somewhat stress the subject's performance, but not to debilitate the subject's response accuracy.

3.5 Muscle Site Selection

Because floating-point hardware for the 68000 is only now becoming available, we were restricted to a single muscle site if we wished to keep the processing time down to a manageable level for this first-phase investigation. It was therefore necessary to ascertain which muscle would provide the most reliable signal for ARIMA modelling. A preliminary set of experiments was run on a single subject while data was collected from four sites : Splenius, trapezius and forearm flexor and extensor. After subjecting the collected myoelectric signals to the ARIMA modelling procedure, we found that the signals collected from the trapezius muscle were the most reliable (i.e., they produced the most repeatable AR coefficients). We therefore decided to conduct this first-phase experiment using the trapezius muscle.

3.6 Subjects and Procedures

An experiment based on the representation described above was conducted. Initially, a single subject participated in a preliminary experiment designed to: (1) evaluate plausible model order and features, and (2) adjust the task parameters. Subsequently, three male subjects were recruited from universities and within Perceptronics' subject pool. All subjects represented the type of personnel who might interface well with perceptual, central processing and tracking tasks. Subject ages ranged from 18 to 30. All had at least a high school diploma and some experience with computers. The subjects were assigned randomly to each of three groups. The subjects were paid $5.50 per hour and were given a bonus of up to $5.50 per hour contingent on performance. The first three subjects, one from each group, had completed the formal experiment in all nine task situations in a balanced order.

The following procedure was followed. Each subject was asked to read an instruction sheet (Appendix B) explaining the experiments to be performed by him. Subjects were encouraged to ask questions as they read the instruction sheet. The subject was then asked to read and fill out a "personal information fact sheet" and a "consent to act as an experimental subject" form. Next, the active electrode assembly was attached to the subject's upper back running approximately parallel to the muscle fibers. A secondary ground electrode was placed on the medial epicondyle of the subject's humerus. Both electrodes were placed on the subject's non-dominant side. Next, the subject underwent an orientation and practice session lasting approximately 2 hours. This was done to reduce the effects of learning during the performance of the actual experiment. The practice session was concluded when the subject produced comparable scores on two successive trials for each task. After a 15 minute break, the actual experiment was performed. The subject was instructed to sit comfortably upright in the chair. The subject was cautioned against moving the side of his body holding the electrodes. For each of three sittings, the subject was required to perform two different tasks, each at two different levels of difficulty. The subject was given a two-minute refresher session just prior to performing a particular task. At this time, a sampled time series is displayed graphically on the screen in order to check signal integrity. Upon task completion, the subject was asked to fill out a questionnaire in which he supplied subjective ratings and post-experimental comments. After completing this form, the subject was instructed to take a 15 minute rest before proceeding to the next task.

Each experimental session consisted of two 200-second trials. Each subject took two days to complete both the orientation session and the six experimental sessions. During each trial, data sampled at 1 KHz was collected in each of three 250 msec windows spaced 60 seconds apart over the 200 second trial. This data collection scheme allowed us to evaluate feature reliability both within and between trials.

3.7 Performance Measures

The performance measures that were collected in the experimental trials are:

(1) Response Time - subject's response measured from the onset of stimulus to the instant when an action is initiated.

(2) Response Accuracy - response errors or incorrect actions as represented by the number of incorrect "key presses," false alarms, missed events; or response precision measures such as RMS tracking error.

These measures were obtained by after analyzing both the sampled and cumulative data. With the exception of RMS tracking error data, which were sampled four times per second, all data were sampled asynchronously. The empirical results along with the statistical and pattern analyses are discussed in the following section.

4. PRELIMINARY EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Overview

This chapter summarizes the preliminary results of the experiments performed in the current phase of this program. The experimental tasks were sufficiently varied to provide a reasonable test of both repeatability and diagnosticity of model-derived features. In our experience thus far, we found that the model parameters converged rapidly. Our preliminary analysis revealed that the first autoregressive coefficient of the model shows a high degree of repeatability for all subjects under all test conditions. The diagnosticity of this feature, however is yet to be established.

The MES data, collected during the experimental trials and the model parameters "fitted" during off-line identification are being examined closely using detailed statistical and pattern analysis methods. The subject's performance data, subjective ratings and comments related to the various task situations will be evaluated in terms of possible correlation with the selected MES features.

4.2 Preliminary MES Features Results

In the following paragraphs, the results and preliminary findings of the first phase effort are discussed. The initial experiments consisted of three subjects, each performing two trials of three different tasks at two levels of difficulty. Analysis of the actual MES data collected during the experiments showed that differencing was not required (i.e., d=0) indicating that in at least this case, the signal is stationary. We

further found that in all cases the autocorrelation function was that of a damped sinusoid or decaying exponential indicating that no moving average terms (i.e., q=0) are necessary to model the signal. We therefore conclude that given our sampling rate of 1 KHz and sampling window size of 250 msec, the process is purely autoregress of order "p." Correlation analysis thus far revealed that the first AR term is in certain cases is strongly coupled to the level of task difficulty. Specifically, the first AR coefficient for a particular subject, task, level of difficulty and trial; is relatively constant for the three records taken during each of the three data collection analysis "windows" during the course of the trial. This is a pervasive finding for all subjects, tasks and levels of difficulty studied. On the basis of these preliminary findings it appears that the first AR coefficient is a good candidate for becoming a "feature" because it is repeatable, i.e., it remains fairly constant for the mental category and the duration of the specific task over which the signal is recorded. On the debit side, while it is true that this parameter is constant for a particular task, trial and load; the absolute value of the parameter does vary from day to day. We feel this variation in the MES from day to day is because the subject's emotional state may be different on any given day giving rise to different levels of muscle tension. In addition, imprecision in electrode placement and variations in the electrode-skin interface are difficult to control over extended periods of time. Since we are more interested in the relative values of the parameter of interest over the course of a trial than we are the absolute value from trial to trial and task to task, we check to see if the relative values follow the same trend from trial to trial and task to task. In almost all cases the value of the first AR coefficient associated with the third recording window decreases with an increase in task difficulty. We choose the last record based on our assumption that most transient effects have stabilized by that point in the trial. We feel that this decrease in the value of the coefficient is correlated with an increase in muscle tension which is expected to occur with an increase in task difficulty. Upon looking at the

curves of the first AR coefficient vs level of difficulty for the first subject (Figure 4-1) it can be seen that for one particular trial and task (trial two of the motor response task), the slope of the curve is much steeper than for the other trials and tasks. In keeping with our hypothesis that a decrease in AR coefficient is associated with an increase in the subjective experience of mental workload, we put forward a plausible argument that in this instance the subject must have experienced a more substantial increase in workload is going from the low to the high level of difficulty than he did for the other tasks and trials. Upon checking the subject's performance results, we observed that this high level of workload was not accompanied by a drop, but rather an unexpected increase in performance. We found corroboration of both our hypotheses and explanation of this performance upon reviewing the subject's answers and comments on the post-experiment questionnaire. His comment read:

> "The higher level of concentration required with this test enables me to keep cursor closer to the center more of the time."

In terms of our hypothesis, this translates to the fact that his workload was indeed higher requiring greater concentration to do the task well. The subject did provide this extra concentration thereby not just maintaining but actually increasing his performance. This can be seen by his specific mention of the "higher level of concentration required" which explains the large drop in the value of the AR coefficient and his statement that "this enabled him to keep the cursor close to the center" which explains the good performance results.

This same trend of a decrease in the first AR coefficient with an increase in task difficulty shows up in the data of the third subject also (Figure 4-2). Unfortunately this finding was not as pervasive among the second subject tested (Figure 4-3). While this subject showed the same downward

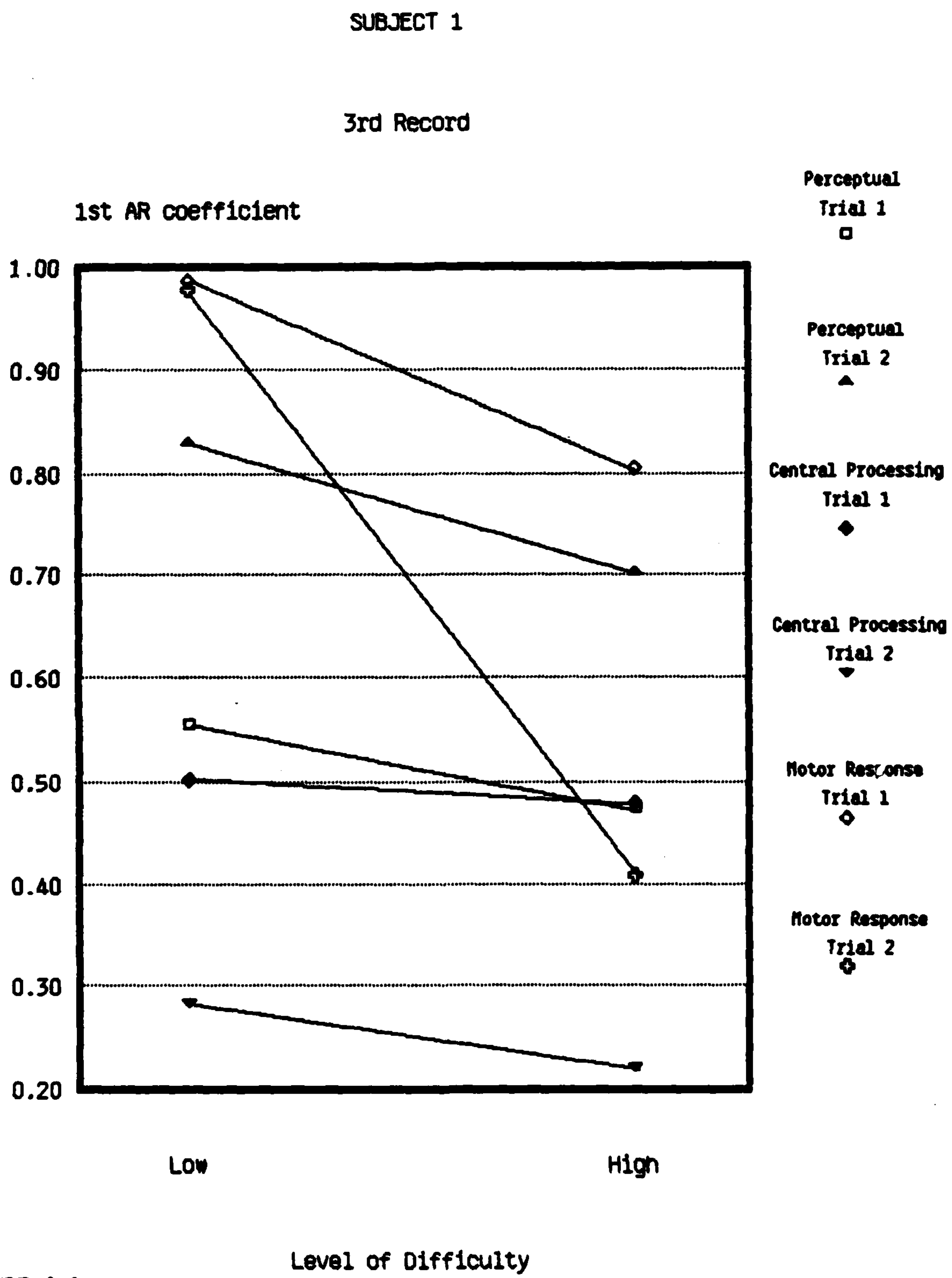

FIGURE 4-1.
FIRST AUTOREGRESSIVE COEFFICIENT VS LEVEL OF DIFFICULTY BY TASK TYPE AND TRIAL NUMBER - SUBJECT 1

SUBJECT 3

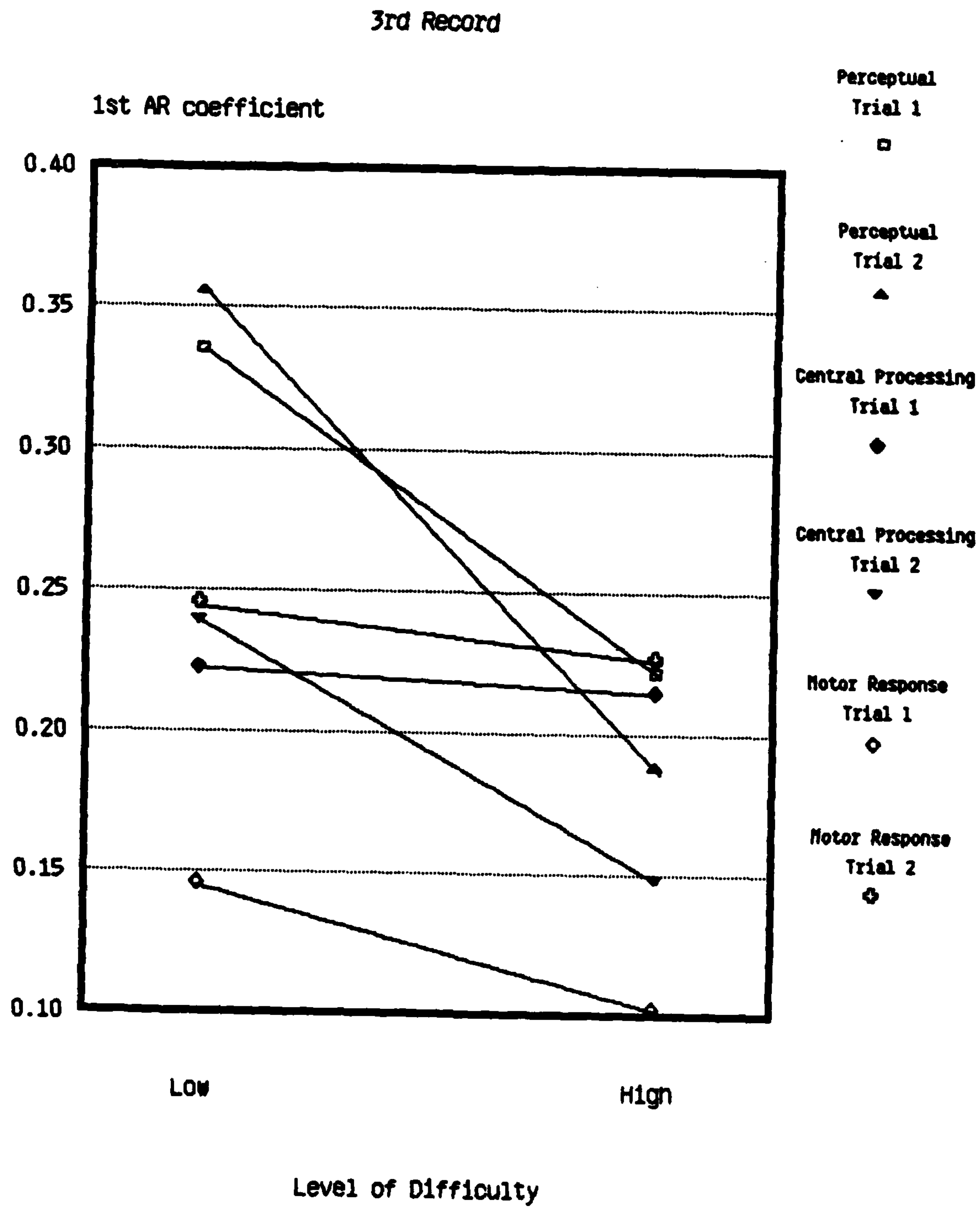

FIGURE 4-2.
FIRST AUTOREGRESSIVE COEFFICIENT VS LEVEL OF DIFFICULTY
BY TASK TYPE AND TRIAL NUMBER - SUBJECT 3

SUBJECT 2

3rd Record

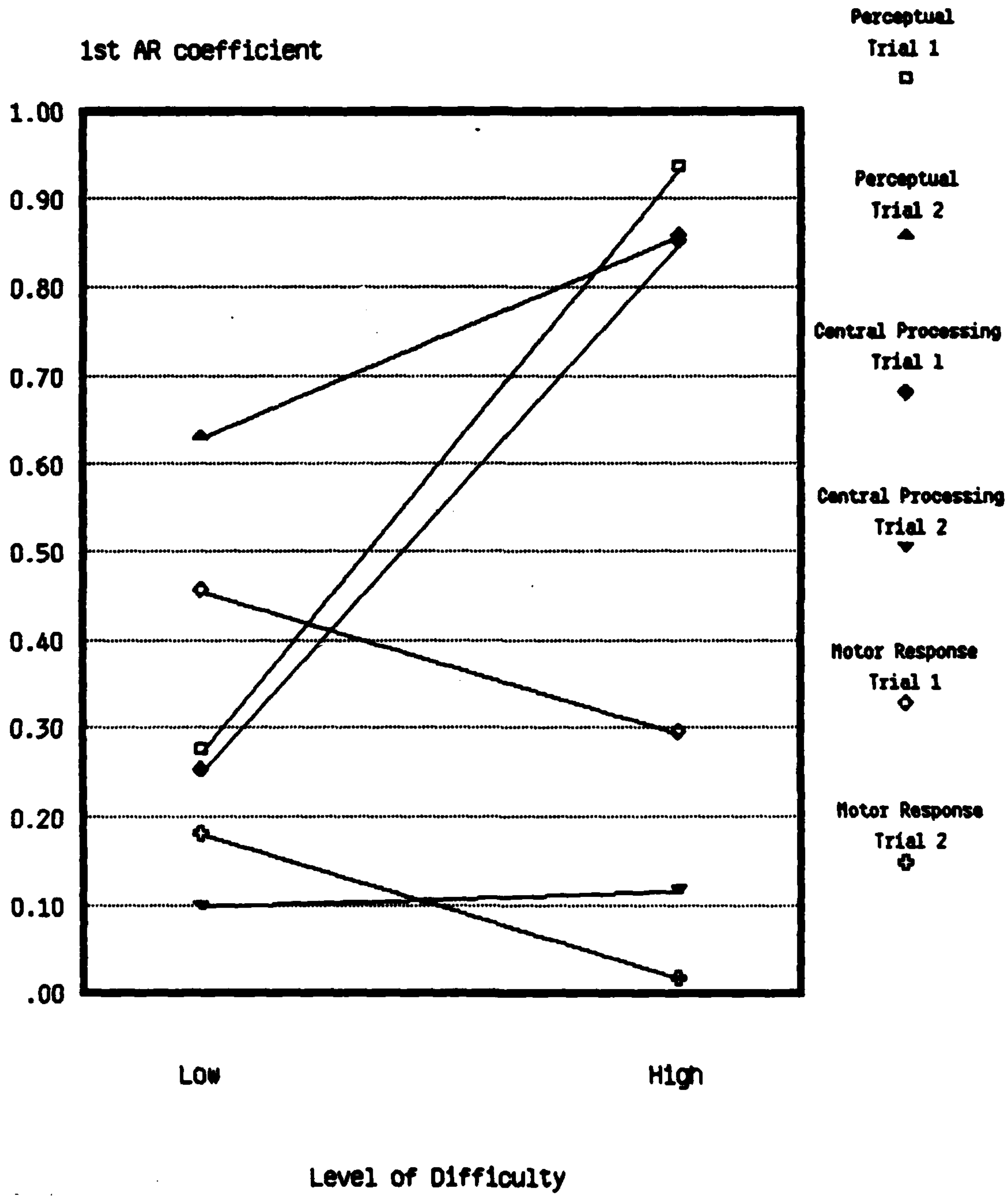

FIGURE 4-3.
FIRST AUTOREGRESSIVE COEFFICIENT VS LEVEL OF DIFFICULTY
BY TASK TYPE AND TRIAL NUMBER - SUBJECT 2

trend for the motor response task, the coefficient of interest increases with an increase in task difficulty for the perceptual and cognitive processing tasks. We put forward the plausible explanation that different people handle increases in workload in different ways. Some people deal with an increase in task load with a corresponding increase in vigilance which in turn causes subconscious increase in muscle tension; others respond to increased load by 'task shedding', that is they reduce the task to one of manageable workload by selectively ignoring events that would raise the workload past the level that they feel comfortable with. In instances like this it is difficult to correlate task load to muscle tension because the applied task related load is different from the load actually perceived by the subject. In this case the first AR coefficient that we are using as a dependent variable is not a good indicator of task difficulty but rather perhaps an indication of the level of vigilance exhibited by the subject in responding to the task!

4.3 Task Performance and Subjective Ratings

Figures 4-4, 4-5, and 4-6 show the task performance scores attained for the three subjects under six different task conditions. It appears that experimental variables generally produced significant effects on performance time, i.e., the subjects' response-time and errors significantly increased as the difficulty level increased from low to high. The effects are more pronounced in the central processing tasks and perceptual task, than that in the tracking control tasks. These effects are confirmed by subjective ratings of task difficulty which show consistent increase with assigned difficulty level. Subject comments and ratings concerning the perceived level of effort in performing the tasks were also analyzed along with the perceived level of difficulty (Table 4-1). Although, the subjects in general perceived themselves as assigning greater effort/attention with increase in task difficulty in order to maintain adequate performance, there is evidence of "task shedding" among the low-score sessions, in which

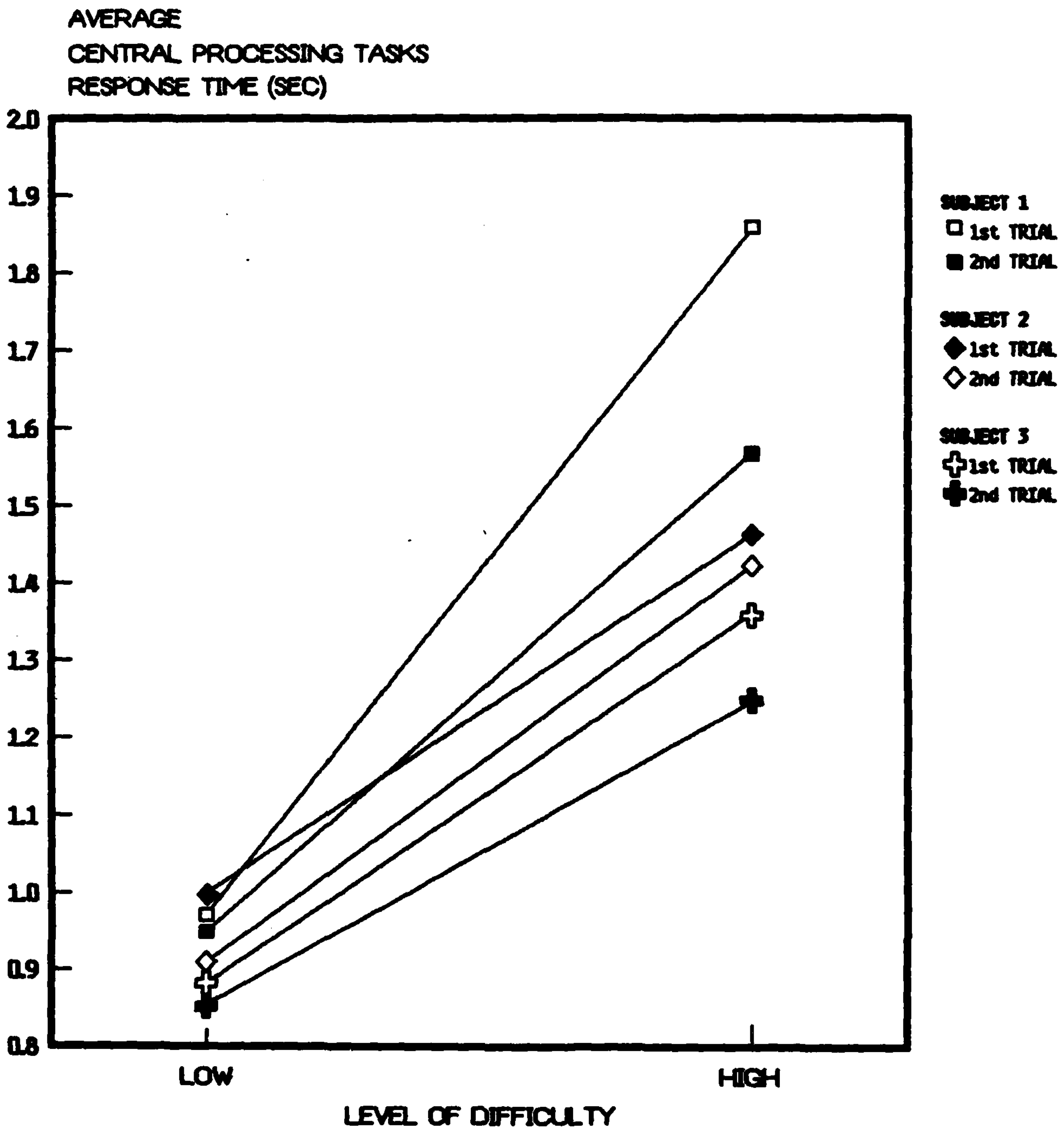

FIGURE 4-4.
CENTRAL PROCESSING TASK RESPONSE TIMES

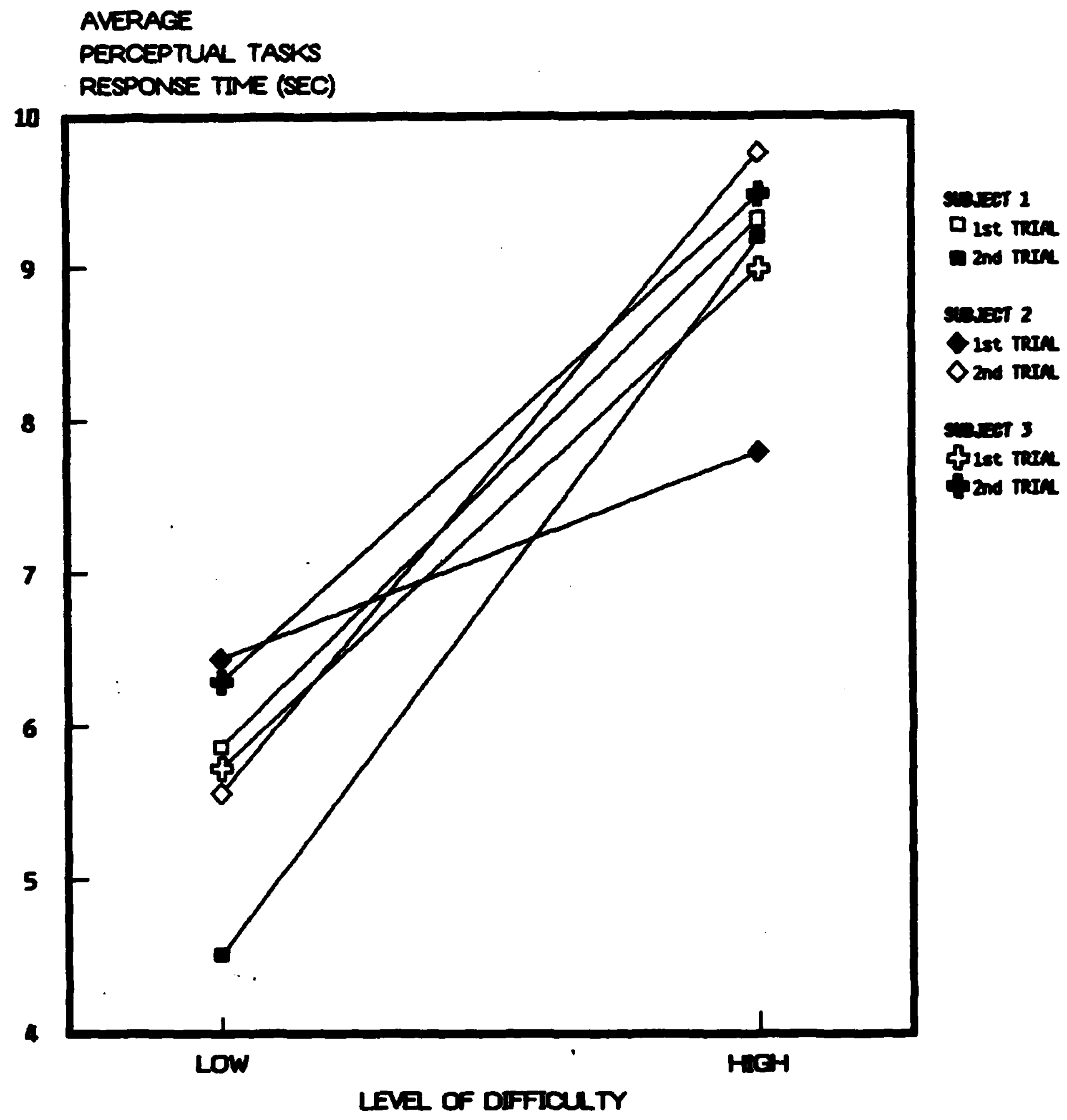

FIGURE 4-5.
PERCEPTUAL TASK RESPONSE TIMES

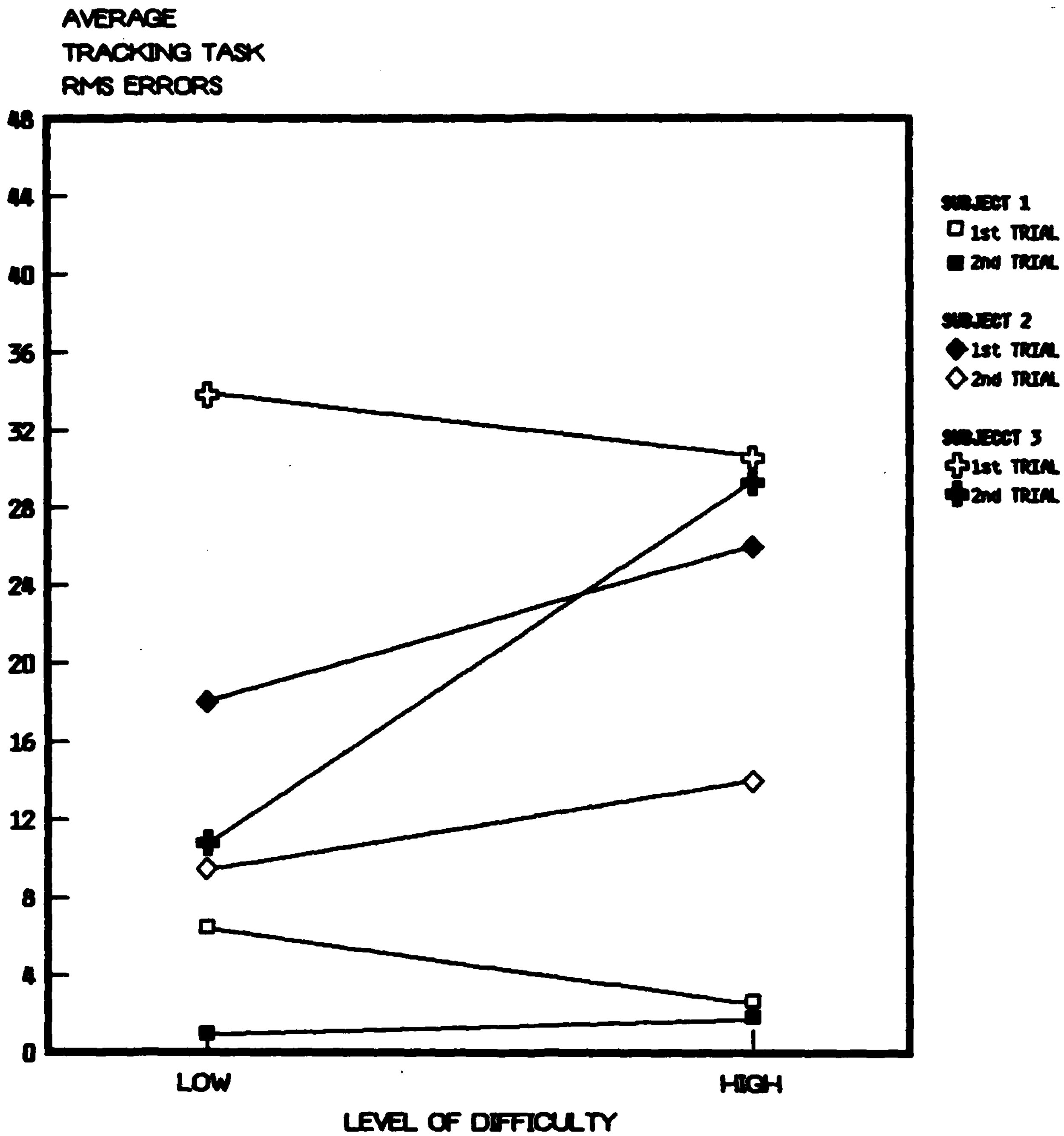

FIGURE 4-6.
TRACKING TASK RMS ERRORS

TABLE 4-1

PERCEIVED LEVEL OF DIFFICULTY BY
SUBJECT, TASK, LOADING LEVEL, AND TRIAL

SUBJECT 1	TRIAL 1		TRIAL 2	
	LOW	HIGH	LOW	HIGH
PERCEPTUAL TASKS				
EFFORT LEVEL	5.8	13.8	5.7	11.7
DIFFICULTY LEVEL	5.9	10.3	6.0	8.2
CENTRAL PROCESSING TASKS				
EFFORT LEVEL	10.3	10.4	10.3	10.7
DIFFICULTY LEVEL	6.2	10.2	6.4	8.5
TRACKING TASKS				
EFFORT LEVEL	11.9	15.5	12.1	15.8
DIFFICULTY LEVEL	8.0	9.8	8.0	10.2
SUBJECT 2	**TRIAL 1**		**TRIAL 2**	
	LOW	HIGH	LOW	HIGH
PERCEPTUAL TASKS				
EFFORT LEVEL	4.5	11.5	4.6	11.3
DIFFICULTY LEVEL	2.6	5.6	5.4	10.7
CENTRAL PROCESSING TASKS				
EFFORT LEVEL	13.0	10.1	6.0	6.9
DIFFICULTY LEVEL	5.6	10.9	5.5	9.2
TRACKING TASKS				
EFFORT LEVEL	6.8	13.1	6.6	12.6
DIFFICULTY LEVEL	5.5	9.4	6.8	9.5
SUBJECT 3	**TRIAL 1**		**TRIAL 2**	
	LOW	HIGH	LOW	HIGH
PERCEPTUAL TASKS				
EFFORT LEVEL	11.1	10.1	9.6	9.9
DIFFICULTY LEVEL	3.8	11.1	6.2	8.8
CENTRAL PROCESSING TASKS				
EFFORT LEVEL	11.3	11.0	9.7	10.1
DIFFICULTY LEVEL	6.8	9.7	6.2	8.4
TRACKING TASKS				
EFFORT LEVEL	11.3	11.5	10.4	12.1
DIFFICULTY LEVEL	6.5	9.5	7.8	9.2

the subjects have demonstrated a lower expenditure of effort for more difficult tasks. This "task shedding" phenomenon has, in certain cases, distorted task loading effects, and, in a few extreme cases, has actually reversed the trend of the actual loading level. When this reversal occurs, mixed trends in the MES feature become apparent.

In order to assess if any statistically significant correlation exists among taskloading, motivation/effort level and MES features, detailed statistical and pattern analysis must be performed.

4.4 Discussions

These preliminary results indicate that the first autoregressive parameter is by far the most useful feature in differentiating workload/alertness level. The data has established this feature's repeatability. Its diagnosticity may be readily demonstrated in the near future with a more refined experiment that the one initially performed.

The overall system approach in the use of ARIMA model-based analysis on non-dominant MES signals has proved to be both technically and operationally feasible, and shows promise for pilot workload/alertness level assessments.

For the next phase of this investigation, there are several hardware and software changes that we are contemplating which will give us more flexibility and allow us to more precisely "tune" the system. These include: use of electrodes which afford easier placement, implementation of floating-point hardware which will provide us with much more flexibility as far as the data analysis is concerned (e.g., differing window size and

sampling rate), simultaneous sampling of signals from multiple muscles, use of statistical and pattern recognition algorithms to help find correlations, and the capability to exert a greater degree of control over the experimental task loading.

It appears from this preliminary study that actual task loading by itself is not sufficient for the evaluation of feature diagnosticity due to the subjective manipulation of mental effort. There are two means of getting around this problem. The first is to provide restrictions on experimental control at the micro level. The second is to provide detailed data/signal analysis capability combined with more sensitive primary task measures. These two methods are currently being evaluated with an eye towards future implementation.

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APPENDIX A

SOFTWARE SPECIFICATIONS

Software Specifications

Overview

There are three packages employed in the MES acquisition and analysis process. Two are used during the performance of the experiment and one is used during the off-line analysis of the MES data.

The two packages used in the performance of the experiment consist of one package for the COSMOS system and one for the Apple. The COSMOS system is used to control the experimental parameters and collect MES data from a subject through the electrodes and A/D board. The second package is used on the Apple IIe to control the presentation of graphic inputs to the subject, record subject responses, and to print a subject performance record.

The third package is comprised of the ARIMA modelling routines and performs analysis of the previously collected MES data in batch mode under control of the experimenter. The experimenter can enter up to 25 files containing MES data records and the package will compute either the autocorrelations and partial autocorrelations of the MES data (step one) or compute the final ARIMA coefficients (step two) for each data record in the selected file.

The two packages running on the COSMOS system are discussed in section A.1. Section A.2 contains specifications of the Apple software.

A.1 Data Acquisition and Analysis Packages

Both packages running on the COSMOS are written in C. The first package which controls the experiment and data acquisition, consists of 4 routines and uses the Analog-to-Digital converter driver. The high-level routine MES-EXP controls the package. It opens up a device communication channel with the Apple and calls two lower level routines (usr-select and set-up) to get session parameters and set up data files for MES data collection. When the operator instructs MES-EXP to start an experiment, a timer is started and the third routine (collect), is called on to collect data at experimenter specified intervals. MES-EXP instructs the Apple to stop generating graphics and recording responses, and to generate a summary report when the session is finished.

The routine usr-select allows the user to specify experiment type, level of difficulty, trial number and the A/D channels used to collect data. By selecting a combination of 1 to 4 channels, a sampling rate of 2000, 1000, 500, or 250 Hz can be selected. The experimenter also supplies the period between sampling windows and the total session length. The data from each window is stored in a separate record within each data file.

The routine set-up allows the experimenter to specify particular files to receive the data from each A/D channel. A header describing the contents of the file may also be supplied.

Finally, the routine collect is responsible for controlling the A/D and collecting data. Currently, 500 data points are collected per window.

The other package running on the COSMOS contains a batch processing routine and the ARIMA routines. The batch processing routine, MES-BATCH, allows the experimenter to control the analysis process. The experimenter can select up to 25 MES data files for analysis. He is then asked which stage

of the ARIMA identification process he would like performed on the specified data files. If the first stage, the identification phase, is specified, the operator is asked the maximum level of differencing desired. If the second stage is specified, the operator is asked to input the values of p, d, and q for each record in each of the specified files.

There are three routines used for the ARIMA analysis -- one for each step of the process. The top-level routine for step 1 is USID which controls the process of computing autocorrelations and partial autocorrelations for an MES data record. These autocorrelations and partial autocorrelations are used by the experimenter to estimate p, d, & q. The top-level routine for step 2 is USPE which controls the calculation for the initial estimates of the autoregressive and moving average parameters. The top-level routine for step 3 is USES which controls the calculation of final autoregressive and moving average parameters. The function of each routine in the ARIMA subsystem is given in Table A-1.

Calling Hierarchies

The calling sequences for all routines are given in Figure A-1.

Experimenter Interface

(1) Performing the Experiment. The experimenter must first boots up the Apple IIe experiment control system. The Apple IIe then waits for a run command to come over its RS-232 serial interface. After booting and logging into the 68000 system, the program MES-EXP is executed. The following messages then appear on the COSMOS system.

TABLE A-1

SUBROUTINES AND ASSOCIATED FUNCTIONS

This list contains the subroutines used by a system with a short statement of function for each routine.

USID	- aids in selection of p, d, & q
diff	- differences a series
mean	- gets the mean of a series
acov	- gets autocovariances
stera	- gets standard errors of autocorrelations
pacor	- gets partial autocorrelations
USPE	- gets initial estimates of and
atoprm	- gets initial estimates of
modcov	- modifies covariances
movarvr	- gets initial estimates of
whtnos	- gets initial estimate for white noise variance
nwtrph	- Newton-Rapson subroutine
gttmat	- gets immediate matrix, tmat, for Newton-Rapson algorithm
matinv	- gets inverse of a matrix
mltmv	- multiplies a matrix by a vector
USES	- gets maximum likelihood estimates of and
calcas	- calculates conditional residuals
ssqr	- gets sum squared of a vector
calcax	- calculates matrix (see 1.4)
calcagd	- calculates matrix a and vector g (see 1.4)
newest	- gets newest estimates of and
check	- checks sum squared of residuals
covest	- gets covariance matrix of estimates
calcscc	- gets standard errors and correlation matrix
rsdac	- gets residual autocorrelations
calchi	- gets chi-square statistic and degrees of freedom
cnchk	- convergence check for Marquardt algorithm

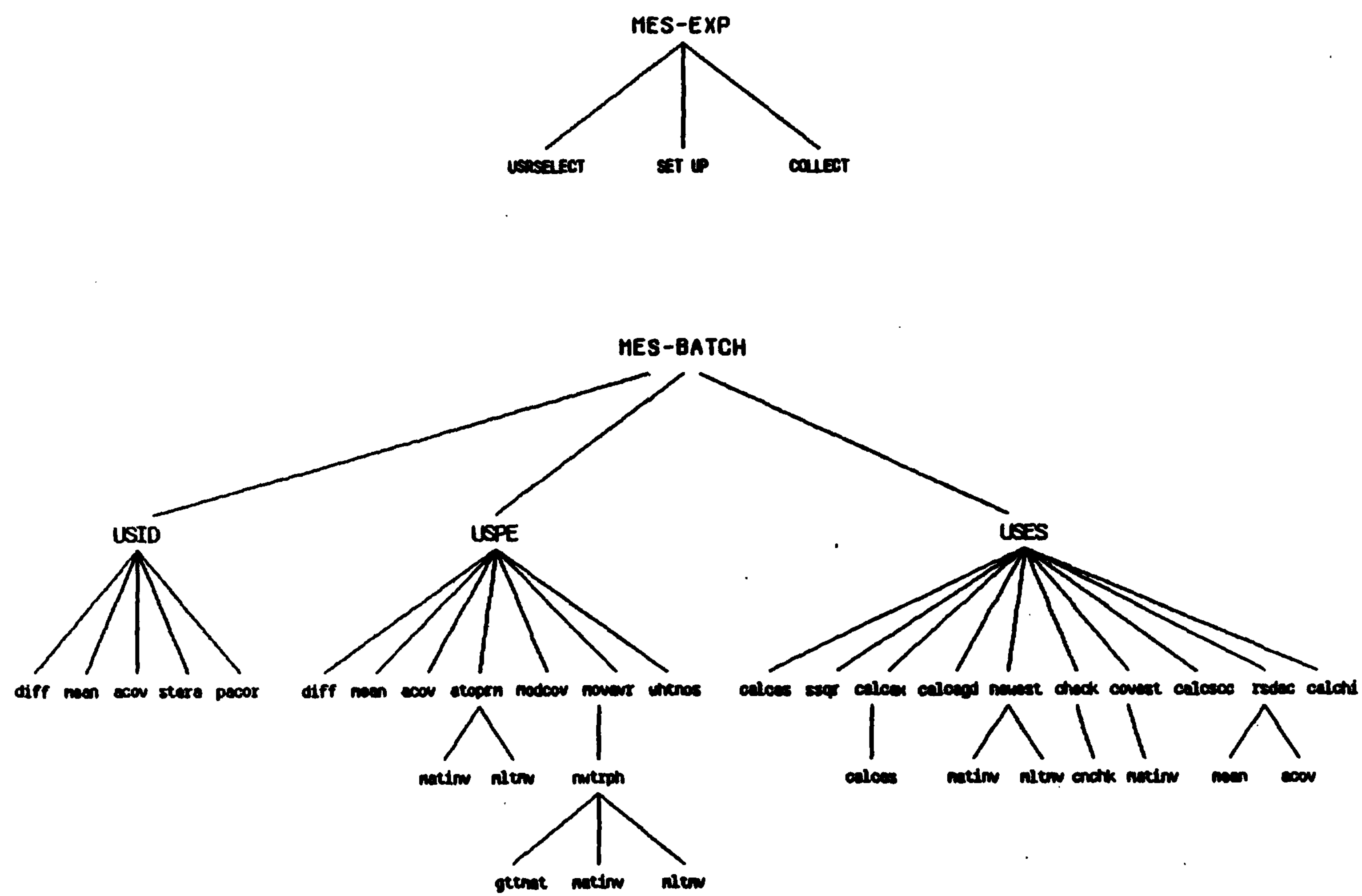

FIGURE A-i.
CALLING HIERARCHIES

MYO-ELECTRIC SIGNAL COLLECTION EXPERIMENT

TYPE TASK TYPE:

'p' - PERCEPTUAL
'c' - CENTRAL PROCESSING
'r' - MOTOR RESPONSE

The experimenter then responds with the character for the desired task. The system then prints:

TYPE TASK LEVEL:

'l'-LOW
'h'-HIGH

The experimenter responds with the character for the desired level of difficulty. The system next types:

TYPE TRIAL NO., '1' or '2'

The experimenter responds by typing '1' or '2'. The system then types:

TYPE EACH A/D CHANNEL USED SEPARATED BY BLANKS
TYPE '-1' FOLLOWED BY RETURN TO TERMINATE

The experimenter types the channels to be used separated by RETURN'S and followed by -1. The system then types:

TYPE PERIOD OF SAMPLINGS IN SECONDS

The user responds with the desired value. Then the system says:

TYPE SESSION LENGTH IN SECONDS

The experimenter responds with the desired value. The system then prints:

TYPE DATA FILE NAME FOR A/D CHANNEL __

The experimenter responds with the file name. The system then responds with:

TYPE HEADER FOR THIS FILE, TERMINATE WITH '*' RETURN

The experimenter types in his header and the file, header sequence is repeated for each A/D channel specified by the experimenter. After the last file and header is specified, the system responds with:

PLACE AND POWER UP ELECTRODES
READY APPLE
PRESS RETURN TO START EXPERIMENT

When both the experimenter and subject are ready to begin the session, the operator presses the return key to initiate the experiment. A run command is then given to the Apple and the two systems begin operating synchronously. When the previously defined session length is reached, the system prints out "EXPERIMENT TERMINATED" on both screens.

(2) Batch Processing ARIMA Analysis. The experimenter runs the ARIMA analysis of the MES data after the experiment has been performed and the data collected. He normally runs the experiment in two stages for a group of MES data files. First he

identifies p, d, & q for any or all of the records in each file. Then he runs the system again to find the final autoregressive and moving average parameters for each record.

When the experimenter runs the 68000 routine MES-BATCH, he sees:

EMG ANALYSIS PROGRAM

TYPE CURRENT DATA FILE NAME

The experimenter then types the current file name. The system then says:

TYPE 'Y' IF YOU WANT TO SPECIFY p, d, & q; OTHERWISE, TYPE 'n'

The experimenter responds. If he types 'y', the system says:

IF YOU WANT TO PROVIDE p, d, & q FOR RECORD 1, TYPE 'y';
OTHERWISE TYPE 'n'

The experimenter responds. If he types 'y' the system prompts as follows with the experimenter's responses underlined:

p = ______
d = ______
q = ______

The system then asks him if he wants to specify p,d, & q for record 2, etc. up until the user types 'n'. The system then says:

TYPE 'y' IF YOU WANT TO SPECIFY ANOTHER FILE; OTHERWISE, TYPE 'n'

If the experimenter responds with 'y', the system types out:

TYPE CURRENT DATA FILE NAME

and the process repeats. When the experimenter finally says he doesn't want to type another file, the system types:

FILES TO BE USED ARE:
(Followed by experimenter specified files.)

The system then prints:

TYPE ONE OF THE FOLLOWING COMMANDS:

'i' - IDENTIFY P, D, & Q
'e' - ESTIMATE PARAMETERS

The experimenter types the desired command and the batch mode analysis program begins writing the results to either a file or the printer.

A.2 Experimental Control Package

The Experimental Control package, implemented in GRAFORTH on the Apple IIe is capable of supporting three separate experiments:

(1) Perceptual experiment.
(2) Control experiment.
(3) Motor response experiment.

(1) Perceptual Experiment. This experiment tests the subject's ability to monitor and respond to a series of ongoing events, on up to four separate displays. This emulates the events displayed to the pilot on aircraft gauges.

Each display consists of a horizontally graduated scale with an initially centered arrow. The arrow oscillates back and forth around the mean using a preset event scheduler which eventually drives the mean off center. The subject is expected to keep the arrow mean centered using dedicated keys. The performance of the subject is measured according to his response time to each individual event.

The arrival time of the event is in accord with a Poisson distribution on a Pre-Set Schedule. There are two levels of difficulty implemented on this experiment.

The subject is presented one or four sets of horizontal scales and oscillating arrows. He responds to a change in the mean of oscillation for any or all of the arrows by pressing the correct arrow key on a dedicated keypad (Figure A-2).

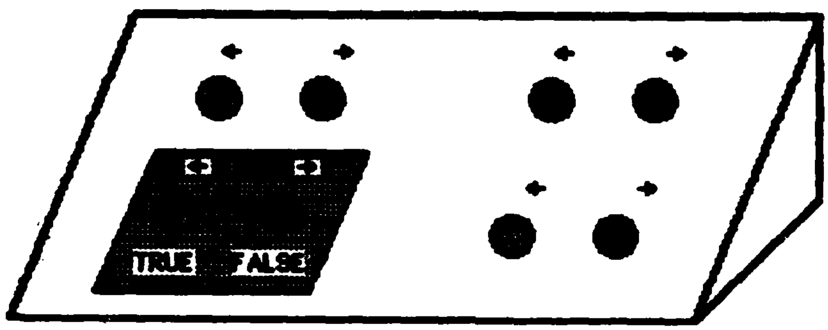

FIGURE A-2.
RESPONSE KEYPAD

Each pair of keys corresponds to the scale and arrow located in the same quadrant on the screen. The correct response to a mean shift is to press the arrow key in the direction in which the mean has shifted.

Performance Evaluation. When an event occurs (i.e., mean about which the arrow oscillates in accord with a preset schedule) it is stored in an event buffer along with its occurrence time. The subjects response to the event (i.e., key presses) is also stored with its time tag. A summary printout of events is given upon termination of the experiment.

(2) Control Processing. In this series of experiments the objective is to measure the subjects ability to match letters or words in a given limited decision time. The experiment is administered at 2 levels of difficulty (i.e., induced cognitive load).

(1) Matching letters (easy).
(2) Matching antonyms (difficult).

From a predefined table of words and letters stored in memory the subject is presented with pairwise letters or words and given two seconds to respond. He is expected to respond by pushing either one of two buttons labled TRUE or FALSE.

The system records the correct response to the event (TRUE, FALSE) as well as the subject's actual response.

Performance Evaluation. Each event associated with the display of a letter pair or word pair is stored in terms of its value and associated occurrence time in the buffer. The event associated with the subject's response is also stored along with its time of occurrence.

The summary printout consists of messages such as EVENT=TRUE or FALSE along with the corresponding time of occurrence with, followed by: RESPONSE=TRUE or FALSE corresponding to the subject's response along with the time of that response. Lack of correspondence between stimulus events and subject's responses are flagged by error messages of the type: ERROR IN RESPONSE X.

(3) <u>Motor Response Experiment</u>. The experiment measures the subject's motor response ability using a deflected object on the screen which is controllable via a joystick interface to the Apple.

A graphic representation of a horizontal bar with a moving block initially at its center is displayed on the screen. The block is continuously deflected in accord with:

$$y(t)_{new} = y(t) + \lambda\,(y(t)+k\;x(t))$$

where

$y_{new}(t)$	= new position of block on scale
$y(t)$	= new old position of block on scale
$x(t)$	= joystick deflection from center
λ	= level of difficulty
k	= constant

The net effect is that the block is always being forced off-center to either end of the bar. The software continuously reads the joystick inputs to the system and incorporates the latest values in computing the new position of the block. this experiment tests the subject's ability to keep the block centered with the help of a joystick control.

The 2 levels of difficulty which are used in the experiment are incorporated in calculating the new position of the block. The higher the level of difficulty, the harder it is to control the block. Throughout the experiment, the following information is collected:

- o Value of off-center distance
- o Edge collisions

For a successful control trial (i.e., no edge collisions), the last 100 sample values of the distance of the block from the bar's center is stored in the memory buffer. Then the RMS distance values are calculated. For a trial in which edge collision(s) have occurred, the elapsed time and the accumulated RMS distance value for the particular control attempt was recorded. At the end of the trial, the time duration and the average RMS values across the control attempts were calculated and printed out in a summary report. A listing of the FORTH "words" used is given in Table A-2.

TABLE A-2

FORTH "Words" AND ASSOCIATED FUNCTIONS

initialize clock	- Initializes the real time clock on Apple 2e
initialize comms	- Initializes the serial communications card on 2e
clear buffer	- Clears the internal buffer
comm	- Initiates communications between 2e and 68000
decode start	- Receives initial starting messages from 68000
decode run	- Decodes interrupts from 68000 key board during experiment
start exp 0	- Sets initial conditions variables to start the perceptual experiment
start exp 1	- Sets initial conditions variables to start the central experiment
start exp 2	- Sets initial conditions variables to start the motor response experiment
maintain exp 0	- Monitors events in perceptual experiment
maintain exp 1	- Monitors events in central experiment
maintain exp 2	- Monitors events in motor response experiment
zero event tab	- Event table for perceptual experiment
zero mean tab	- Table of means for perceptual experiment
set seed	- Sets up a random number generator
board	- Draws graphic scale for motor response experiment
narrow	- Draws graphic displays for perceptual experiment
get - key	- Reads subject response to various experiments
arrowmean	- Subroutine to oscillate arrow in perceptual experiment
good/bad	- Determines if events in central experiment are true or false
net dot	- Calculates continuous new positions for block in motor experiment

TABLE A-2 (Cont'd)

edge test	- Checks for edge collision in motor response experiment
get RMS	- Calculates the RMS values in motor response
store events	- Stores all events (key strokes, etc) in internal buffer
ptime	- Reads clock and stores event time
printen	- Prints contents of buffer in a readable format
stick pos	- Reads joystick values
draw dot	- draws graphic for motor response experiment

APPENDIX B

SUBJECT'S INSTRUCTIONS

AFOSR/OPERA EXPERIMENT SUBJECT'S INSTRUCTIONS

This experiment is part of a program of continuing research at Perceptronics in human (pilot) performance and decision making. The purpose of this particular experiment is to analyze ways in which human operators' myoelectric (muscle) signals respond and how a computer might help to determine an operator's mental state via these signals. You are an integral part of this research since your performance provides the baseline data for predicting operator performance, and estimating the effectiveness of computer-based analysis techniques.

Tasks Overview

There are three types of tasks that you will be asked to perform in the experiment. They are: (1) perceptual (or probability monitoring) task, (2) central processing (or linguistic processing) task, and (3) motor (or control) tracking task. Within each task, there are two difficulty levels -- low and high. You will be given direction as to the specific type and difficulty level of the task and the approximate time it will take to complete. Please concentrate on the task as your response and performance will be closely monitored and scored based on both your response time and response accuracy. (We will have a bonus for the best performer after we have completed the experiment.) At the end of each run, you will be given a questionnaire to fill out. Information on these questionnaires will not be used to rate your score, so please use your unbiased judgment to answer those questions.

The following paragraphs describe the three types of tasks.

Perceptual (Probability Monitoring) Task. In this task, you will be asked to monitor a hypothetical instrument panel of one or four gauges, each with a moving arrow. The arrow has a set range of fluctuation around the center of the dial. Occasionally, a particular arrow will start to drift to the right or left, fluctuating not about the center but around one of the divisions to the right or left of center. This signifies an abnormal event occuring in the underlying instrument, and you can correct the event and the drifting by hitting one of the right or left buttons for the corresponding

dial. If the arrow has drifted to the right, press the right arrow button and visa versa. If you do it correctly, the arrow will move back to the center again. Please respond to any detected event as soon as possible and try not to make mistakes in button selection, not to make a false alarm (guess about the event) or miss an event. The performance will be evaluated by the combined score of average response time and percentage of incorrect actions (including mistakes, false alarms and missed events).

Central Processing (Linguistic Processing) Task. In this task, you will see a sequence of letter pairs or word pairs shown on the screen every two to three seconds. You will be asked to compare and classify them as "same" (true event) or "different" (false event) based on (1) the character catagories (e.g., aa, cc are the same pairs; ae, ac are different pairs. Upper and lower case representations of the same letter [e.g., Aa] are classified as different); or (2) the antonym catagories (true event if the two words are antonyms [i.e., opposites] and false event if otherwise). Please respond as soon as you can and, at the same time, avoid making any mistakes. A decision needs to be made before the next pair appears so that you don't miss any response opportunities. Missed events and incorrect responses will be registered as errors.

Motor (Control) Tracking Task. In this task, you will see a cursor which moves on a horizontal axis. You will be asked to use a joystick to maintain the cursor as close to the center as possible. A tone will be given when the cursor moves off the scale and the cursor will start from the center again. Performance will be measured as (1) the average time until loss of control and (2) the closeness of the cursor to the center of the axis averaged over the entire trial.

APPENDIX C

SAMPLE PRINTOUT

EMG ANALYSIS PROGRAM

FILE IS ps2.data
Robert 4/16/84 14:30

NO. OF RECORDS = 3 NO. OF SAMPLES = 500

RECORD = 1

DATA:

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-31	-37	-40	-27	-41	-40	-26	-26	-21	-23
-12	-8	-23	-28	-23	-29	-31	-42	-51	-48
-58	-57	-56	-52	-29	-14	27	26	36	51
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-53	-42	-46	-45	-47	-49	-39	-58	-50	-47
-40	-49	-31	-49	-51	-41	-39	-55	-39	-51
-57	-50	-73	-60	-64	-76	-61	-73	-60	-81

UNIVARIATE STOCHASTIC MODEL IDENTIFICATION

TIME SERIES:

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-12	-8	-23	-28	-23	-29	-31	-42	-51	-48
-58	-57	-56	-52	-29	-14	27	26	36	51
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-57	-50	-73	-60	-64	-76	-61	-73	-60	-81

NUMBER OF OBSERVATIONS = 500

MAXIMUM LAG OF ACVF, ACF = 20

MAXIMUM LAG OF PACF = 20

LEVEL OF DIFFERENCING = 0

DIFFERENCED AND TRANSFORMED SERIES:

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22	26	11	6	11	5	3	-8	-17	-14
-24	-23	-22	-18	5	20	61	60	70	85
87	90	75	36	17	-14	-10	-10	-8	3
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-14	-14	-8	-15	0	-8	-7	-7	-12	-1
-15	0	-20	-23	-18	-14	-5	-6	-18	-20
-15	-25	-10	-17	-5	-3	-11	-3	-15	5
-2	-12	11	14	7	1	3	16	7	15
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20	40	71	55	71	82	89	72	29	1
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-23	-16	-39	-26	-30	-42	-27	-39	-26	-47

NUMBER OF DIFFERENCED VALUES = 500

AUTOCOVARIANCES:

6.618940e+02	5.766620e+02	5.067000e+02	3.962780e+02	2.628940e+02
1.607760e+02	3.327000e+01	-5.451800e+01	-1.173140e+02	-1.652680e+02
-1.618740e+02	-1.611400e+02	-1.262180e+02	-8.240400e+01	-4.988200e+01
4.100000e-01	1.761200e+01	3.443400e+01	4.930400e+01	3.698800e+01
4.790600e+01				

AUTOCORRELATIONS:

1.000000e+00	8.712301e-01	7.655304e-01	5.987031e-01	3.971844e-01
2.429029e-01	5.026484e-02	-8.236666e-02	-1.772399e-01	-2.496895e-01
-2.445618e-01	-2.434529e-01	-1.906922e-01	-1.244973e-01	-7.536252e-02
6.194345e-04	2.660849e-02	5.202343e-02	7.448927e-02	5.588206e-02
7.237715e-02				

STANDARD ERRORS OF AUTOCORRELATIONS:

0.000000e+00	7.096595e-02	8.590875e-02	9.388340e-02	9.718598e-02
9.839269e-02	9.844404e-02	9.858177e-02	9.921704e-02	1.004659e-01
1.016496e-01	1.028091e-01	1.035141e-01	1.038131e-01	1.039225e-01
1.039225e-01	1.039361e-01	1.039882e-01	1.040948e-01	1.041548e-01
1.042554e-01				

PARTIAL AUTOCORRELATIONS:

8.712301e-01	2.692793e-02	-3.062949e-01	-3.110078e-01	8.840510e-02
-1.811273e-01	1.199930e-02	8.347133e-02	-1.612088e-03	9.745529e-02
-4.618127e-02	4.914805e-02	1.381621e-02	-6.271049e-02	2.364367e-02
-8.022220e-02	-2.601486e-02	7.078087e-02	-2.924550e-02	9.288832e-02

STANDARD ERROR OF PARTIAL AUTOCORRELATIONS = 4.472136e-02

Apr 29 13:04 1984 Estimation Page 1

EMG ANALYSIS PROGRAM

FILE IS ps2.data
Robert 4/16/84 14:30

NO. OF RECORDS =   3 NO. OF SAMPLES = 500

RECORD =   1

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-12	-8	-23	-28	-23	-29	-31	-42	-51	-48
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-46	-44	-41	-51	-43	-44	-41	-44	-47	-50
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51	56	26	16	-30	-49	-35	-45	-50	-38
-45	-30	-49	-52	-56	-45	-45	-39	-34	-45
-42	-56	-44	-42	-41	-42	-35	-50	-44	-49
-43	-49	-44	-39	-49	-45	-39	-55	-34	-31
-43	-40	-36	-42	-44	-51	-35	-43	-43	-42

-39	-48	-51	-41	-39	-44	-34	-47	-30	-41
-40	-33	-35	-18	-31	-36	-26	-38	-23	-29
-23	-42	-50	-40	-54	-62	-58	-60	-26	-18
17	12	37	49	56	64	51	33	7	-37
-53	-42	-46	-45	-47	-49	-39	-58	-50	-47
-40	-49	-31	-49	-51	-41	-39	-55	-39	-51
-57	-50	-73	-60	-64	-76	-61	-73	-60	-81

UNIVARIATE STOCHASTIC MODEL PRELIMINARY ESTIMATION

TIME SERIES:

-47	-36	-50	-49	-27	-35	-37	-41	-51	-37
-31	-37	-40	-27	-41	-40	-26	-26	-21	-23
-12	-8	-23	-28	-23	-29	-31	-42	-51	-48
-58	-57	-56	-52	-29	-14	27	26	36	51
53	56	41	2	-17	-48	-44	-44	-42	-31
-44	-56	-33	-60	-41	-46	-46	-36	-42	-39
-46	-44	-41	-51	-43	-44	-41	-44	-47	-50
-48	-48	-42	-49	-34	-42	-41	-41	-46	-35
-49	-34	-54	-57	-52	-48	-39	-40	-52	-54
-49	-59	-44	-51	-39	-37	-45	-37	-49	-29
-36	-46	-23	-20	-27	-33	-31	-18	-27	-19
-34	-42	-33	-64	-69	-66	-64	-49	-52	-36
-14	6	37	21	37	48	55	38	-5	-33
-45	-47	-30	-46	-33	-35	-58	-33	-49	-39
-48	-47	-33	-48	-50	-38	-52	-46	-42	-55
-31	-60	-49	-43	-61	-47	-47	-36	-36	-41
-36	-42	-45	-42	-51	-47	-53	-44	-50	-51
-40	-37	-31	-48	-41	-41	-32	-31	-45	-43
-36	-50	-33	-38	-34	-41	-28	-27	-43	-33
-24	-38	-19	-26	-25	-42	-35	-39	-51	-53
-59	-65	-57	-52	-29	-14	9	37	31	49
56	56	41	-5	-32	-36	-48	-42	-56	-49
-40	-49	-42	-45	-30	-47	-44	-37	-51	-37
-48	-49	-47	-52	-50	-40	-46	-38	-47	-52
-25	-58	-45	-49	-52	-36	-44	-50	-33	-32
-50	-46	-43	-45	-38	-32	-46	-38	-48	-46
-39	-46	-39	-37	-35	-27	-45	-38	-51	-44
-25	-38	-29	-21	-24	-20	-35	-34	-27	-31
-30	-43	-46	-51	-57	-63	-60	-60	-38	-35
-7	7	27	52	44	55	59	22	0	-43
-43	-51	-40	-46	-58	-43	-55	-37	-35	-45
-44	-41	-46	-38	-47	-36	-43	-46	-32	-52
-42	-48	-43	-36	-50	-43	-39	-52	-53	-50
-49	-36	-44	-36	-50	-42	-32	-45	-33	-49
-51	-45	-49	-50	-51	-47	-52	-42	-51	-57
-44	-41	-36	-22	-45	-38	-39	-17	-27	-34
-29	-20	-20	-28	-37	-38	-39	-55	-40	-63
-72	-71	-69	-37	-39	0	13	29	48	37
51	56	26	16	-30	-49	-35	-45	-50	-38
-45	-30	-49	-52	-56	-45	-45	-39	-34	-45

-42	-56	-44	-42	-41	-42	-35	-50	-44	-49
-43	-49	-44	-39	-49	-45	-39	-55	-34	-31
-43	-40	-36	-42	-44	-51	-35	-43	-43	-42
-39	-48	-51	-41	-39	-44	-34	-47	-30	-41
-40	-33	-35	-18	-31	-36	-26	-38	-23	-29
-23	-42	-50	-40	-54	-62	-58	-60	-26	-18
17	12	37	49	56	64	51	33	7	-37
-53	-42	-46	-45	-47	-49	-39	-58	-50	-47
-40	-49	-31	-49	-51	-41	-39	-55	-39	-51
-57	-50	-73	-60	-64	-76	-61	-73	-60	-81

NUMBER OF DIFFERENCINGS =   0

NUMBER OF AUTOREGRESSIVE PARAMETERS =   6

NUMBER OF MOVING AVERAGE PARAMETERS =   0

DIFFERENCED AND TRANSFORMED SERIES:

-13	-2	-16	-15	7	-1	-3	-7	-17	-3
3	-3	-6	7	-7	-6	8	8	13	11
22	26	11	6	11	5	3	-8	-17	-14
-24	-23	-22	-18	5	20	61	60	70	85
87	90	75	36	17	-14	-10	-10	-8	3
-10	-22	1	-26	-7	-12	-12	-2	-8	-5
-12	-10	-7	-17	-9	-10	-7	-10	-13	-16
-14	-14	-8	-15	0	-8	-7	-7	-12	-1
-15	0	-20	-23	-18	-14	-5	-6	-18	-20
-15	-25	-10	-17	-5	-3	-11	-3	-15	5
-2	-12	11	14	7	1	3	16	7	15
0	-8	1	-30	-35	-32	-30	-15	-18	-2
20	40	71	55	71	82	89	72	29	1
-11	-13	4	-12	1	-1	-24	1	-15	-5
-14	-13	1	-14	-16	-4	-18	-12	-8	-21
3	-26	-15	-9	-27	-13	-13	-2	-2	-7
-2	-8	-11	-8	-17	-13	-19	-10	-16	-17
-6	-3	3	-14	-7	-7	2	3	-11	-9
-2	-16	1	-4	0	-7	6	7	-9	1
10	-4	15	8	9	-8	-1	-5	-17	-19
-25	-31	-23	-18	5	20	43	71	65	83
90	90	75	29	2	-2	-14	-8	-22	-15
-6	-15	-8	-11	4	-13	-10	-3	-17	-3
-14	-15	-13	-18	-16	-6	-12	-4	-13	-18
9	-24	-11	-15	-18	-2	-10	-16	1	2
-16	-12	-9	-11	-4	2	-12	-4	-14	-12
-5	-12	-5	-3	-1	7	-11	-4	-17	-10
9	-4	5	13	10	14	-1	0	7	3
4	-9	-12	-17	-23	-29	-26	-26	-4	-1
27	41	61	86	78	89	93	56	34	-9
-9	-17	-6	-12	-24	-9	-21	-3	-1	-11
-10	-7	-12	-4	-13	-2	-9	-12	2	-18
-8	-14	-9	-2	-16	-9	-5	-18	-19	-16
-15	-2	-10	-2	-16	-8	2	-11	1	-15
-17	-11	-15	-16	-17	-13	-18	-8	-17	-23
-10	-7	-2	12	-11	-4	-5	17	7	0
5	14	14	6	-3	-4	-5	-21	-6	-29

-38	-37	-35	-3	-5	34	47	63	82	71
85	90	60	50	4	-15	-1	-11	-16	-4
-11	4	-15	-18	-22	-11	-11	-5	0	-11
-8	-22	-10	-8	-7	-8	-1	-16	-10	-15
-9	-15	-10	-5	-15	-11	-5	-21	0	3
-9	-6	-2	-8	-10	-17	-1	-9	-9	-8
-5	-14	-17	-7	-5	-10	0	-13	4	-7
-6	1	-1	16	3	-2	8	-4	11	5
11	-8	-16	-6	-20	-28	-24	-26	8	16
51	46	71	83	90	98	85	67	41	-3
-19	-8	-12	-11	-13	-15	-5	-24	-16	-13
-6	-15	3	-15	-17	-7	-5	-21	-5	-17
-23	-16	-39	-26	-30	-42	-27	-39	-26	-47

AUTOCOVARIANCES:

6.618940e+02   5.766620e+02   5.067000e+02   3.962780e+02   2.628940e+02
1.607760e+02   3.327000e+01

INITIAL ESTIMATES OF AUTOREGRESSIVE PARAMETERS:

8.042637e-01   3.107581e-01   -8.655653e-02   -3.095668e-01   2.311791e-01
-1.811271e-01

INITIAL ESTIMATES OF MOVING AVERAGE PARAMETERS:

INITIAL ESTIMATE OF WHITE NOISE VARIANCE = 1.251865e+02

UNIVARIATE STOCHASTIC MODEL ESTIMATION

h[1] = 1.120436e-02 phi2[1] = 8.154680e-01
h[2] = -4.626880e-03 phi2[2] = 3.061312e-01
h[3] = -8.433133e-04 phi2[3] = -8.739984e-02
h[4] = -7.891212e-03 phi2[4] = -3.174580e-01
h[5] = 1.182190e-02 phi2[5] = 2.430010e-01
h[6] = -4.118866e-03 phi2[6] = -1.852460e-01

S(B0) = 5.994822e+04 S(B) = 5.990726e+04

h[1] = 6.477033e-03 phi2[1] = 8.219450e-01
h[2] = -5.424129e-03 phi2[2] = 3.007071e-01
h[3] = -1.283012e-03 phi2[3] = -8.868285e-02
h[4] = -5.048565e-03 phi2[4] = -3.225065e-01
h[5] = 1.012739e-02 phi2[5] = 2.531284e-01
h[6] = -3.846748e-03 phi2[6] = -1.890927e-01

S(B0) = 5.990726e+04 S(B) = 5.989479e+04

h[1] = 3.048000e-03 phi2[1] = 8.249929e-01
h[2] = -3.067821e-03 phi2[2] = 2.976393e-01
h[3] = -6.991340e-04 phi2[3] = -8.938198e-02
h[4] = -1.771282e-03 phi2[4] = -3.242778e-01
h[5] = 5.258203e-03 phi2[5] = 2.583866e-01
h[6] = -2.474323e-03 phi2[6] = -1.915670e-01

-38	-37	-35	-3	-5	34	47	3	32	71
85	90	60	50	4	-15	-1	-1	-16	-4
-11	4	-15	-18	-22	-11	-11	5	0	-11
-8	-22	-10	-8	-7	-8	-1	-6	-10	-15
-9	-15	-10	-5	-15	-11	-5	-1	0	3
-9	-6	-2	-8	-10	-17	-1	-9	-9	-8
-5	-14	-17	-7	-5	-10	0	-3	4	-7
-6	1	-1	16	3	-2	8	4	11	5
11	-8	-16	-6	-20	-28	-24	-5	8	16
51	46	71	83	90	98	85	7	41	-3
-19	-8	-12	-11	-13	-15	-5	-4	-16	-13
-6	-15	3	-15	-17	-7	-5	-1	-5	-17
-23	-16	-39	-26	-30	-42	-27	-9	-26	-47

AUTOCOVARIANCES:

6.618940e+02 5.766620e+02 5.067000e+02 3.962780e+02 2.628940e+02
1.607760e+02 3.327000e+01

INITIAL ESTIMATES OF AUTOREGRESSIVE PARAMETERS:

8.042637e-01 3.107581e-01 -8.655653e-02 -3.095668e-01 2.311791e-01
-1.811271e-01

INITIAL ESTIMATES OF MOVING AVERAGE PARAMETERS:

INITIAL ESTIMATE OF WHITE NOISE VARIANCE = 1.251865e+02

UNIVARIATE STOCHASTIC MODEL ESTIMATION

```
h[1] =  1.120436e-02 phi2[1] =  8.154680e-01
h[2] = -4.626880e-03 phi2[2] =  3.061312e-01
h[3] = -8.433133e-04 phi2[3] = -8.739984e-02
h[4] = -7.891212e-03 phi2[4] = -3.174580e-01
h[5] =  1.182190e-02 phi2[5] =  2.430010e-01
h[6] = -4.118866e-03 phi2[6] = -1.852460e-01

S(B0) =  5.994822e+04 S(B) =  5.990726e+04

h[1] =  6.477033e-03 phi2[1] =  8.219450e-01
h[2] = -5.424129e-03 phi2[2] =  3.007071e-01
h[3] = -1.283012e-03 phi2[3] = -8.868285e-02
h[4] = -5.048565e-03 phi2[4] = -3.225065e-01
h[5] =  1.012739e-02 phi2[5] =  2.531284e-01
h[6] = -3.846748e-03 phi2[6] = -1.890927e-01

S(B0) =  5.990726e+04 S(B) =  5.989479e+04

h[1] =  3.048000e-03 phi2[1] =  8.249929e-01
h[2] = -3.067821e-03 phi2[2] =  2.976393e-01
h[3] = -6.991340e-04 phi2[3] = -8.938198e-02
h[4] = -1.771282e-03 phi2[4] = -3.242778e-01
h[5] =  5.258203e-03 phi2[5] =  2.583866e-01
h[6] = -2.474323e-03 phi2[6] = -1.915670e-01
```

```
S(B0) =  5.989479e+04 S(B) =  5.989257e+04

h[1] =  8.952189e-04 phi2[1] =  8.258881e-01
h[2] = -9.962639e-04 phi2[2] =  2.966430e-01
h[3] = -2.281227e-04 phi2[3] = -8.961010e-02
h[4] = -3.307642e-04 phi2[4] = -3.246086e-01
h[5] =  1.568982e-03 phi2[5] =  2.599556e-01
h[6] = -8.572481e-04 phi2[6] = -1.924243e-01

S(B0) =  5.989257e+04 S(B) =  5.989244e+04

h[1] =  1.178491e-04 phi2[1] =  8.260059e-01
h[2] = -1.658523e-04 phi2[2] =  2.964771e-01
h[3] =  1.45766[illegible]-06 phi2[3] = -8.960864e-02
h[4] = -3.272739e-05 phi2[4] = -3.246413e-01
h[5] =  2.015861e-04 phi2[5] =  2.601571e-01
h[6] = -1.188248e-04 phi2[6] = -1.925431e-01

S(B0) =  5.9892[illegible]e+04 S(B)    5.989241e+04
```

FINAL AUTOREGRESSIVE PARAMETERS:

8.258881e-01	2.966430e-01	-8.961010e-02	-3.246086e-01	2.599556e-01
-1.924243e-01				

FINAL MOVING AVERAGE PARAMETERS:

FINAL RESIDUALS:

0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
0.000000e+00	-1.277010e+01	-4.693109e+00	-7.325656e+00	7.817104e+00
1.052642e+01	-7.795923e+00	-8.957023e+00	1.521253e+01	-1.278771e+01
-5.163909e+00	1.506859e+01	5.800202e+00	-1.764403e+00	-1.738007e-01
1.258538e+01	5.094998e+00	-1.233386e+01	-7.095396e+00	1.189485e+01
-4.144789e-02	-2.809669e+00	-6.883995e+00	-6.707145e+00	2.600148e+00
-6.320801e+00	-2.963669e+00	-1.112595e-03	3.177014e+00	1.690865e+01
1.531770e+01	3.560544e+01	-4.136733e-01	6.212603e+00	1.658422e+01
1.697524e+01	6.673498e+00	1.342141e+00	-2.390309e+01	-7.300859e+00
-9.043783e+00	1.743602e+01	1.344268e+01	1.256253e+01	9.640941e+00
-7.336115e+00	-1.868840e+01	2.048324e+01	-2.006661e+01	6.639677e+00
-2.381016e+00	1.776683e+00	-2.090010e+00	8.151793e-01	-5.953575e+00
-7.799441e+00	8.381496e-01	-1.550263e-02	-9.255919e+00	2.085577e+00
7.599121e-01	4.235004e-01	-7.681743e+00	-3.409921e+00	-7.101993e+00
7.699441e-01	-2.206850e+00	3.314347e+00	-9.232991e+00	1.062018e+01
-8.251165e+00	-3.388477e+00	-4.329063e+00	-2.499223e+00	4.876654e+00
-1.143428e+01	9.617676e+00	-1.906255e+01	-6.378500e+00	1.002103e-02
9.603479e+00	4.624388e-01	-1.597426e+00	-1.652846e+01	-8.093284e+00
4.872372e+00	-1.163361e+01	8.059300e+00	-5.636712e+00	6.632618e+00
-2.788096e+00	-8.196051e+00	-1.202749e+00	-8.656132e+00	1.434727e+01
-5.701574e+00	-1.186718e+01	1.574606e+01	1.324083e+01	-1.373618e+01
-1.036178e+01	7.657464e+00	1.322888e+01	-6.264978e+00	5.940184e+00
-1.097022e+01	-7.216078e+00	7.641499e+00	-2.232451e+01	-1.378924e+01
6.184477e+00	6.526872e+00	4.595255e+00	-2.950121e+00	7.565567e+00
1.749267e+01	1.923450e+01	2.413604e+01	-1.256795e+01	1.164735e+01
2.080928e+01	2.164155e+01	-1.237285e+01	-2.710535e+01	-1.758935e+01

7.259324e+00	1.440138e+01	2.591183e+01	-5.792459e+00	1.030881e+01
9.242917e-01	-2.198488e+01	1.377092e+01	-4.582294e+00	2.047380e+00
-1.266953e+01	5.072614e+00	5.694227e+00	-9.755354e+00	-1.203024e+01
1.191416e+01	-1.019461e+01	-4.687194e+00	5.529854e+00	-1.227924e+01
1.375955e+01	-2.295084e+01	7.603100e-01	4.323641e+00	-1.255372e+01
-2.635986e+00	7.406402e+00	6.148254e+00	-6.967991e+00	-4.852798e+00
-1.840662e+00	-4.222253e+00	-7.057701e+00	1.141495e+00	-7.061078e+00
-9.963971e-01	-5.813303e+00	6.748107e+00	-8.825201e+00	-3.862013e+00
5.830930e+00	4.756051e+00	-5.160924e-01	-1.940869e+01	2.796479e+00
5.177436e-01	9.202321e+00	-3.104205e+00	-1.275383e+01	-3.772450e+00
1.008683e+01	-1.355720e+01	1.003529e+01	2.564862e-01	1.146864e+00
-1.212946e+01	1.552182e+01	-5.160060e-01	-1.595609e+01	3.852194e+00
1.623851e+01	-1.399646e+01	1.184011e+01	1.705530e+00	-1.160878e+00
-2.016755e+01	1.148739e+01	-3.066639e+00	-9.562599e+00	-6.963371e+00
-1.226391e+00	-9.142433e+00	3.905020e+00	5.240565e+00	1.746358e+01
1.192906e+01	1.916805e+01	2.417287e+01	-2.725015e+00	1.383761e+01
1.825299e+01	1.259096e+01	-7.673199e+00	-2.786703e+01	-1.598803e+01
1.625632e+01	7.925008e+00	1.157010e+01	-3.876786e+00	8.699315e+00
8.557823e+00	-6.908787e+00	-2.931656e+00	-1.170411e+00	1.183211e+01
-1.995311e+01	-1.287818e+00	5.096264e+00	-1.010228e+01	3.657524e+00
-5.845200e+00	-4.946794e+00	-3.390229e+00	-1.200205e+00	-5.657672e+00
9.581826e+00	-6.925882e+00	9.068572e-01	-9.690443e+00	-8.404202e+00
2.194954e+01	-2.659186e+01	-9.506350e-01	-1.222538e+00	5.999141e-01
2.736074e+00	4.725583e-02	-1.538861e+01	1.294113e+01	6.167916e+00
-2.557199e+01	-2.268496e+00	8.395819e+00	-4.130579e+00	1.158010e+00
8.408967e+00	-1.633171e+01	1.418745e+00	-7.128252e+00	-7.539434e-01
3.520306e+00	-3.359504e+00	-4.952386e-01	3.215483e+00	6.880418e-01
3.363150e+00	-1.621910e+01	9.355188e-01	-1.031297e+01	6.195900e+00
1.636056e+01	-7.081887e+00	-1.857526e+00	1.126708e+01	-3.283800e-01
-3.229466e+00	-9.969246e+00	-2.805756e-01	9.379967e+00	1.575653e+00
-2.593909e+00	-9.612313e+00	-3.404912e+00	-4.906978e+00	-4.341139e+00
-9.420988e+00	2.464165e+00	-2.115993e+00	1.723126e+01	9.305229e-01
2.135572e+01	1.137794e+01	1.949699e+01	2.159011e+01	8.071075e-01
1.063337e+01	1.840267e+01	-2.027078e+01	-1.716105e+01	-2.019634e+01
1.542694e+01	7.277494e+00	2.427803e+01	-3.792439e+00	-7.872306e+00
8.932803e+00	-6.783122e+00	9.256010e+00	1.074991e+00	-1.015763e+01
-9.982780e+00	7.185765e+00	-7.823715e+00	3.203045e+00	-7.343000e+00
7.058423e+00	-7.850162e+00	-4.664589e+00	8.912042e+00	-1.493804e+01
2.942968e-01	-3.814653e+00	5.359460e+00	1.971565e-01	-1.046580e+01
-1.927508e+00	6.178566e+00	-1.363809e+01	-9.862933e+00	5.436359e+00
-1.247871e-01	7.157021e+00	-7.782824e+00	1.789796e+00	-1.592691e+01
5.082721e+00	7.561632e+00	-1.014690e+01	2.176532e+00	-1.120602e+01
-6.243958e+00	1.949352e+00	1.352516e+00	-9.117727e+00	-1.748445e+00
2.404419e+00	-8.935114e+00	5.787901e+00	-1.046367e+01	-1.107919e+01
7.586730e+00	6.139112e+00	-2.215724e+00	1.024603e+01	-2.148296e+01
-2.752629e+00	1.688175e+00	2.439854e+01	-1.299033e+01	-7.402029e+00
1.746983e+00	1.654625e+01	-2.154754e+00	-7.815860e+00	-7.883775e+00
1.197090e+00	1.598405e+00	-1.495060e+01	1.262880e+01	-1.762724e+01
-1.531169e+01	-3.837966e+00	6.780893e+00	2.158186e+01	-1.406366e+00
2.817050e+01	1.107912e+01	1.465427e+01	1.149555e+01	5.595406e-01
1.313865e+01	2.086074e+01	-1.389761e+01	-4.780710e+00	-2.211440e+01
-6.978419e+00	2.711883e+01	1.258525e+01	-8.116625e+00	1.609993e+01
4.085509e-01	6.640474e+00	-1.792557e+01	-7.039772e+00	-7.935588e+00
1.455321e+01	-5.027685e+00	4.202495e+00	1.058249e+00	-1.181780e+01
-4.307798e+00	-1.301002e+01	8.740080e+00	1.535330e+00	8.647546e-01
-7.920150e+00	7.900266e+00	-1.765888e+01	6.771135e-01	-4.401015e+00

5.329054e+00	-1.048664e+01	4.434735e+00	1.553673e+00	-1.019466e+01
-3.440457e+00	7.007790e+00	-1.686148e+01	1.234756e+01	8.147967e+00
-1.500937e+01	-7.090604e+00	1.039089e+01	-8.441939e+00	-7.038613e+00
-5.577973e+00	1.446834e+01	-7.258784e+00	-4.345025e+00	-2.445015e+00
5.640793e+00	-1.423664e+01	-5.445533e+00	8.755960e+00	3.294389e+00
-1.010157e+01	6.273735e+00	-1.102857e+01	1.076588e+01	-9.740470e+00
-9.328520e-01	2.246115e+00	4.004555e+00	1.017798e+01	-9.186220e+00
-8.776189e+00	8.456496e+00	-4.098870e+00	8.373299e+00	-5.316117e-01
6.943098e+00	-2.134519e+01	-6.058004e+00	8.566897e+00	-6.627681e+00
-1.563040e+01	3.522639e+00	1.007359e+00	2.607221e+01	9.910493e+00
2.872244e+01	-7.738468e+00	2.405164e+01	1.339754e+01	1.844684e+01
1.016407e+01	5.705628e+00	-6.869404e+00	-9.466780e+00	-2.473277e+01
-3.246551e+00	3.076594e+01	1.222248e+01	8.416312e-01	1.429302e+00
-3.106884e-01	4.787249e+00	-1.857646e+01	2.908857e-01	3.27[illegible]217e+00
7.1[illegible]5964e+00	-1.699926e+01	1.608632e+01	-1.824448e+01	-8.49[illegible]774e+00
5.9[illegible]7660e+00	8.198607e+00	-2.485278e+01	1.215785e+01	-7.82[illegible]485e+00
-1.2[illegible]3306e+01	7.263334e-01	-1.761246e+01	6.354136e-01	-2.400469e+00
-1.549140e+01	1.330522e+00	-8.310662e+00	-2.858751e-02	-2.72[illegible]523e+01

RESIDUAL VARIANCE = 1.212398e+02

COVARIANCE MATRIX OF ESTIMATES:

1.973300e-03	-1.591023e-03	-7.274519e-04	1.378755e-04	7.93[illegible]071e-04
-2.106788e-04	-1.591023e-03	3.221223e-03	-9.083985e-04	-8.14[illegible]543e-04
-5.921103e-04	7.968030e-04	-7.274527e-04	-9.083981e-04	3.16[illegible]512e-03
-1.025503e-03	-7.986488e-04	1.223604e-04	1.378757e-04	-8.14[illegible]539e-04
-1.025503e-03	3.165146e-03	-9.251953e-04	-7.153397e-04	7.93[illegible]071e-04
-5.921111e-04	-7.986479e-04	-9.251951e-04	3.221667e-03	-1.58[illegible]941e-03
-2.106787e-04	7.968032e-04	1.223602e-04	-7.153401e-04	-1.58[illegible]941e-03
1.970880e-03				

STANDARD ERRORS:

4.442183e-02	5.675582e-02	5.622733e-02	5.625963e-02	5.67[illegible]973e-02
4.439459e-02				

CORRELATION MATRIX OF ESTIMATES:

1.000000e+00	-6.310583e-01	-2.912462e-01	5.516880[illegible]02	3.14[illegible]521e-01
-1.068302e-01	-6.310582e-01	1.000000e+00	-2.846548[illegible]01	-2.55[illegible]074e-01
-1.838027e-01	3.162354e-01	-2.912465e-01	-2.846547[illegible]01	1.00[illegible]000e+00
-3.241847e-01	-2.502465e-01	4.901887e-02	5.516889[illegible]02	-2.55[illegible]072e-01
-3.241848e-01	1.000000e+00	-2.897318e-01	-2.864081[illegible]01	3.14[illegible]522e-01
-1.838029e-01	-2.502462e-01	-2.897317e-01	1.000000[illegible]00	-6.28[illegible]917e-01
-1.068302e-01	3.162354e-01	4.901880e-02	-2.864083[illegible]01	-6.28[illegible]914e-01
1.000000e+00				

RESIDUAL AUTOCORRELATIONS:

1.000000e+00	3.473442e-03	1.985737e-02	-3.923553[illegible]03	5.20[illegible]324e-02
3.722751e-03	2.157055e-02	-4.653008e-02	1.455601[illegible]02	-4.47[illegible]301e-02
5.233048e-02	-3.696466e-02	9.024374e-03	5.127612[illegible]02	1.70[illegible]783e-02
9.209155e-02	4.766153e-02	-4.973612e-02	4.768314[illegible]02	-1.05[illegible]030e-01
4.555550e-02	-1.138014e-01	4.626628e-02	-6.736232[illegible]04	-2.059[illegible]56e-02
1.318120e-02	-3.754254e-02	-8.796880e-02	-4.394097[illegible]02	-3.851[illegible]20e-02

7.966785e-02	-5.035416e-02	-6.580636e-02	-1.884099e-02	-1.130112e-01
-2.076864e-02	-3.354269e-02	-4.958485e-02	3.921619e-02	-7.593057e-02
2.563546e-02	-7.401919e-02	-6.940793e-02	-6.597688e-02	-3.252554e-02
7.372040e-02	-4.327371e-02	-5.277649e-02	1.597528e-02	-1.207157e-01
4.900131e-02	-4.673372e-02	-5.761386e-02	1.716637e-02	-4.443517e-02
2.659655e-02	-2.804325e-02			

CHI-SQUARE STATISTIC = 8.137434e+01

DEGREES OF FREEDOM =   50